VOLUME 49 • SPECIAL ISSUE • NO 2 • JANUARY 2026

ISSN 0971-3034

THE INDIAN JOURNAL OF TECHNICAL EDUCATION

Published by

INDIAN SOCIETY FOR TECHNICAL EDUCATION

Near Katwaria Sarai, Shaheed Jeet Singh Marg,

New Delhi - 110 016

INDIAN JOURNAL OF TECHNICAL EDUCATION

Volume 49 • Special Issue • No. 2 • January 2026

www.ijteonline.in

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INDIAN JOURNAL OF TECHNICAL EDUCATION

Published by
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Editorial

Artificial Intelligence in the Era of Responsible Innovation: Artificial Intelligence (AI) has evolved from a specialized academic field into a transformative technological force influencing nearly every dimension of modern society. Its ability to process vast volumes of structured and unstructured data, identify intricate patterns, and assist in complex decision-making has significantly reshaped traditional operational frameworks. Across sectors, AI-driven systems enhance productivity, improve accuracy, and support evidence-based strategies. What was once considered an experimental research domain has now become a mainstream technological foundation for innovation and competitiveness.

In engineering and applied sciences, AI technologies are accelerating research cycles, refining design precision, and enabling solutions that were previously unattainable through conventional computational approaches. Intelligent algorithms integrated into laboratories, universities, and industrial environments represent a major shift in how knowledge is generated, validated, and implemented. Machine learning models assist in structural health monitoring, optimize manufacturing processes, and strengthen renewable energy forecasting. Real-time analytics embedded in smart infrastructure promotes safer transportation systems and more resilient urban development strategies.

Within mechanical and electrical engineering domains, predictive maintenance tools detect performance irregularities before system breakdowns occur, reducing downtime and operational expenditure. However, the rapid integration of AI demands rigorous validation standards, transparency in algorithm development, and responsible data governance. Ethical oversight and regulatory clarity are essential to ensure that innovation progresses responsibly. Without comprehensive frameworks, technological advancement may exceed society's readiness to address concerns related to bias, accountability, cybersecurity, and privacy protection.

AI is also reshaping scholarly communication and academic publishing. Editorial management systems increasingly employ intelligent tools to streamline manuscript screening, identify ethical risks, and enhance language quality. While these applications improve efficiency, they cannot substitute for critical scholarly judgment or intellectual responsibility. Authors remain accountable for originality, methodological rigor, and meaningful contribution. Clear institutional policies regarding AI-assisted writing are necessary to safeguard academic integrity. Ultimately, the sustainable impact of AI depends on harmonizing computational intelligence with human insight, ethical reflection, and socially responsible innovation that promotes transparency, inclusivity, and long-term global progress

Artificial Intelligence Expands Capability; Human Wisdom Defines Direction.

New Delhi **Editor-in-Chief**

31st January 2026

Thadomal Shahani Engineering College

DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND DATA SCIENCE,

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Contents

Comparative Analysis on Medical Data Processing with RAG-Augmented Fine-Tuned LLMs and Guardrails

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ABSTRACT

One of the novel methods for the improvement of accuracy and reliability in medical data processing is the combination of state-of-the-art Large Language Models (LLMs) with Retrieval-Augmented Generation (RAG) and guardrail mechanisms. We explore the performance of various fine-tuned LLMs intended for healthcare applications. The models are examined in respect of their ability for proper retrieval of patient medical records, clinical sense, factual accuracy, and the avoidance of the dangers of misinformation and hallucinated output. We give particular emphasis to the inclusion of guardrails, which are of the utmost importance to make medical AI systems ethical and regulatory compliant. Guardrails put limits, identify outliers, and stop the creation of potentially harmful or non-compliant content. At the same time, the RAG framework enhances contextual knowledge of the system by including domain knowledge in response generation, thus improving accuracy and relevance. Our research compares the performance of different RAG and LLM configurations according to their strengths and weaknesses, as well as best application scenarios. The findings demonstrate the potential combination of RAG and LLMs in facilitating secure and trustworthy medical decision-making.

KEYWORDS *: Guardrails, Hallucinations, Healthcare, Large language models (LLMs), Medical data, Retrieval-augmented generation (RAG).*

INTRODUCTION

Robust language models that can support healthcare professionals in decision-making, documentation, and patient communication have been developed as a result of the rapid advancement of artificial intelligence (AI) in medicine. The ability of Large Language Models (LLMs) trained on medical data to comprehend complex medical queries, summarise patient histories, and deliver precise responses has shown progress.

The comparison of many fine-tuned LLMs combined with RAG and guardrails is presented in order to evaluate how well they handle medical data. We want to determine the best approach for AI-based medical applications by measuring performance measures such as accuracy, dependability, and clinical relevance. Our results contribute to the field of study on AI-enabled healthcare by providing the most effective way to optimise LLMs for real-world medical use cases while maintaining safety and compliance.

The system proposed in this paper incorporates three major modules: Guardrailing, Retrieval Augmented Generation, and Fine-Tuning to improve the reliability and correctness of the response produced by a fine-tuned model. The process starts with a user input, which is used as the system input. The Guardrailing module is the first processing layer that ensures the input is in line with pre-specified ethical and safety standards.

Fig. 1: Block diagram of the system

After passing the Guardrailing Module to perform safety and ethics checks, the prompt goes through the RAG Module, which retrieves relevant context from formal medical sources in order to aid fact-based and context-sensitive answers. Domain-specific fine-tuning is then applied to the LLM output using the context that was

recovered, wherein a model specific to a domain fine-tunes the output according to medical training data.

This paper includes a study of four language models: Gemma1.1-7B, Llama2-7B, Llama3-8B, and Mistral-7B, analyzing their performance in medical query handling and response reliability.

Gemma1.1-7B is an efficient and compact large language model that is tasked with providing natural language processing powers that are fast and scalable. In the research, Gemma1.1-7B was assessed for its coherence and context-based response generation against computational efficiency.

Llama2-7B is a Meta-built, openly weighted language model with strong capabilities in reasoning and knowledge-based functions. In this work, Llama2-7B was tested for its retrieval-augmented generation (RAG) feature and ability to be fine-tuned with medical knowledge.

Llama3-8B is an advanced version of Meta's Llama series, bringing contextual comprehension and response accuracy improvements, especially in dealing with domain-specific questions. In this research, Llama3-8B was experimented upon for its performance in combining retrieved knowledge with fine-tuned information to provide more accurate and reliable results in medical applications.

Mistral-7B is a cutting-edge transformer-based model renowned for its maximized training efficiency and enhanced text generation performance. Mistral-7B was examined in this research based on its performance in medical query management, especially on its ability to reduce hallucinations while ensuring high response dependability.

The paper also tests three guardrail mechanisms: NeMo-Guardrails, Guardrails AI, and Llama Guard to guarantee safe, ethical, and dependable response generation in medical use.

NeMo-Guardrails, built by NVIDIA, provides a programmable and modular architecture that can specify conversation flows, apply response rules, and prevent toxic or out-of-scope content in real time. It was utilized to enforce bespoke safeguards against misinformation and unethical suggestions, which are essential in healthcare situations.

Guardrails AI is a Python framework for specifying what LLMs can and cannot output using structured XML-like configuration, which makes it ideal for establishing clear boundaries in medical conversation. It was tested for data privacy enforcement, medical sensitivity enforcement, and rejection of ambiguous or dangerous outputs.

Llama Guard, proposed by Meta, is a light safety classifier model specifically tailored for pre-screening or post-processing LLM output. It was incorporated into the system for marking unsafe or toxic replies, especially in user inputs, and proved highly effective in screening out inappropriate content during medical consultations.

LITERATURE REVIEW

Rebedea et al. [1] introduced NeMo Guardrails, a collection of tools designed to provide controlled and secure LLM applications. The system works towards reducing hallucinations, dealing with output ambiguity, and increasing credibility, making it ideal for safety-critical environments such as medicine.

Christophe et al. [2] introduce Med42-v2, a set of clinical LLMs that were fine-tuned on multiple medical corpora. Their approach indicates better accuracy in clinical decision support, especially with respect to complex medical terminologies.

Xu et al. [3] present CHATQA 2, utilizing the wider context window of Llama-3.0 for more complex RAG features. Their research highlights the model's ability to process ultra-long contexts, which can increase retrieval efficiency for medical use cases.

Ayyamperumal and Ge [4] reflect on the current risks of LLMs and the importance of AI guardrails. Their contribution denotes the dangers of LLM hallucinations, which is crucial in using LLMs for sensitive medical inquiries.

Gentner et al. [5] systematically review medical chatbot studies focused on behavioral change models. Their observations are useful to inform responsive and user-centered medical chatbots.

Gupta et al. [6] introduce Florence, a health chatbot intended for patient interaction. The study emphasises the prospects of chatbots in enhancing patient communication and personalized health guidance.

Vakayil et al. [7] designed a RAG-based LLM chatbot with Llama-2 to assist victims of sexual harassment. The empathetic and non-judgmental nature of the project's focus can be used to develop sensitive and ethical medical chatbots.

Sanna et al. [8] propose a modular RAG architecture for mitigation of unstructured data constraints in certified medical chatbots. Efficient streamlining of trusted medical data retrieval in multilingual settings can be utilized with the modular design.

Kirubakaran et al. [9] design a RAG-based medical assistance for infectious diseases. A knowledge graph incorporation to avoid hallucinations can lead to best practices in the retrieval of medical information.

Bora and Cuayáhuitl [10] critically examine RAG-based LLMs for medical chatbots. They contrast fine-tuning and RAG strategies and find that the hybrid method enhances the model's accuracy, which is applicable for deploying solid medical query systems.

The various researches highlight Guardrails' relevance to avoid hallucinations, Fine-Tuning that boosts domain know-how, and RAG increasing response reliability using extensive medical knowledge bases. Building on these outcomes, our study aims to combine guardrailing, RAG, and fine-tuning for creating a reliable, accurate, and safe medical AI system withstanding healthcare processes in the real world.

METHODOLOGY

Our system's methodology is systematic in its approach towards creating an intelligent and trustworthy medical query system. It incorporates carefully curated medical knowledge, security features, model fine-tuning, dynamic retrieval methods, and a user-friendly interface. The system begins by processing requests made by users through a Guardrailing Module, which eliminates unsafe or inapt requests for safety. A request found to be safe is then converted to embeddings and passed on to the Retrieval-Augmented Generation (RAG) module. Within this module, appropriate context is fetched from a structured medical knowledge base to enhance the accuracy of responses. The refined answer is then ultimately displayed to the user, delivering reliable, context-aware, and medically relevant outputs.

Fig.2. depicts the structured workflow of the medical query system, which leverages Guardrails, Retrieval-Augmented Generation (RAG), and a well-tuned Large Language Model (LLM) to yield correct and safe responses. The system ultimately offers a properly formatted medical response, ensuring safety, accuracy, and reliability. This structured pipeline ensures safety, reliability, and retrieval-augmented response generation, where the system is efficient and robust in handling medical queries.

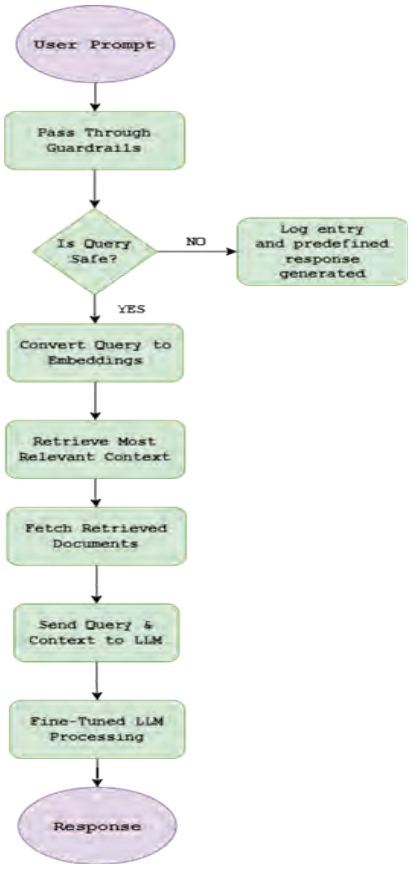

Fig. 2: Workflow diagram of the system

The following are key elements of the system that provide accuracy, safety, and usability, such as structured data collection, ethical control guardrails, retrieval-based augmentation, domain-specific fine-tuning, and a user-friendly interface.

Data Collection and Knowledge Base Construction

The platform is constructed upon a sound medical knowledge base developed with research articles, medical papers, journals, and open source data sets. Medical data like clinical guidelines, research articles, and patient information are collected and categorized to create a rich repository of verified data. In this manner, the model is guaranteed to have access to up-to-date and contextually relevant medical information.

Guardrails Mechanism

These guardrails watch the inputs and outputs of the model to keep it from producing inappropriate, biased, or wrong information. If the system detects a potentially dangerous answer, it corrects it or puts out a disclaimer to adhere

to ethical standards. These are similar to a filtering layer which imposes ethical standards, manages ambiguity, and holds answers accountable according to medical best practices.

Retrieval-Augmented Generation (RAG) Framework

RAG improves the model's output by bringing in outside knowledge dynamically. Instead of being limited to leveraging pre-trained data, the system pulls in the relevant medical documents dynamically, resulting in more dependable responses less prone to relying on stale or erroneous data. This guarantees that responses are accurate and contextually rich.

Fine-Tuning Model

Fine-tuning the model with clinical domain data enhances its ability to learn complex medical sentences, diagnostic patterns, and treatment processes. This refinement enhances the language model to perform optimally within clinical use, improving accuracy and relevance to the context. Through fine-tuned expertise, the model generates more precise and domain-relevant responses.

Evaluation Metrics

A comparative analysis of various evaluation metrics utilized in measuring the performance of fine-tuned models and guardrailing agents. The measurements are carried out based on BLEU, ROUGE-L, BERTScore, and QAG Score, each handling unique aspects of text similarity, fluency, and relevance.

1. BLEU Score: BLEU (Bilingual Evaluation Understudy) is an accuracy-oriented metric that measures the similarity between a generated text and a reference text based on comparing n-grams. It estimates the percentage of n-grams in the candidate text that overlap with the reference text and adds a brevity penalty to prevent short output. Introduced by Papineni et al. (2002), BLEU is a popular tool for assessing the quality of machine translation.

$$BLEU = BP \times exp(\Sigma (w_n \log p_n))$$

Where:

- *BP is brevity penalty to avoid translations*
- P_n : *precision for n-grams*
- W_n: *weight for n-grams*

ROUGE-L Score: ROUGE-L (Recall-Oriented Understudy for Gisting Evaluation) calculates longest common subsequence (LCS) between the reference and candidate text as a function of recall and precision. It calculates how much the reference text is preserved in the generated text, making it suitable for summarization and text generation applications where sequence structure has to be preserved.

$$\text{ROUGE-}L_F = \frac{(1+\beta^2).ROUGE\text{-}L_P.ROUGE\text{-}L_R}{\beta^2.ROUGE\text{-}L_P + ROUGE\text{-}L_R}$$

Where:

- $\text{ROUGE-}L_F = \frac{LCS(X,Y)}{length\ of\ candidate}$ (Precision)
- $\text{ROUGE-}L_R = \frac{LCS(X,Y)}{length\ of\ reference}$ (Recall)
- β: *balancing factor, often set to 1 for equal weight on precision and recall.*
- LCS(X,Y): *longest common subsequence between candidate X and reference Y.*

BERTScore: BERT (Bidirectional Encoder Representations from Transformers) Score utilizes contextual representations of a pre-trained BERT model to determine semantic similarity between candidate and reference text words. Unlike traditional n-gram-based metrics, which lose meaning outside of literal word matches, BERTScore maintains meaning outside of literal word matches through contextual representations and is thus best suited to evaluate fluency and coherence in text generation.

$$R_{BERT} = \frac{1}{|X|} \sum_{xi \epsilon X} max_{yi \epsilon Y} (xi \cdot yi)$$

Where:

- X and Y are the sets of token embeddings for the candidate and reference sentences, respectively.
- xi and yi represent token embeddings from the candidate and reference text.
- xi · yi is the dot product (cosine similarity) between embeddings.
- $\max_{yi \epsilon Y}$ xi. yi finds the most similar reference token for each candidate token.
- The summation averages across all tokens in X, normalizing by the number of tokens $|X|$.

QAG Score: QAG (Question-Answer Generation) Score is a collective measure developed to evaluate question-answer generation models. It presents itself as BLEU,

ROUGE-L, and BERTScore along with weighted contributions in order to reflect the quality of the text as a whole. This measure ensures generated text remains semantically sound as well as concurs with linguistic quality and contextual coherence.

QAG = α·BLEU+β·ROUGE-L+γ·BERTScore

Where:

- α,β,γ: weighting factors for BLEU, ROUGE-L, and BERTScore
- BLEU: measures n-gram overlap
- ROUGE-L: evaluates sequence similarity
- BERTScore: contextual similarity metric

RESULTS AND DISCUSSIONS

Comparative Evaluation of Language Model Performance

Table 1 shows the comparative performance analysis of various language models: Gemma1.1-7B, Llama2-7B, Llama3-8B, and Mistral-7B, tested on the four most important NLP performance criteria: BLEU, ROUGE-L, BERTScore, and QAG. Each metric tests various attributes of text generation quality such as precision, recall, contextual similarity, and question-answering ability.

Table 1: Evaluation Metrics of Different Models

Models	BLEU	ROUGE-L	BERT	QAG
Gemma1.1-7B	0.90	0.92	0.94	0.91
Llama2-7B	0.78	0.85	0.89	0.82
Llama3-8B	0.79	0.86	0.91	0.84
Mistral-7B	0.80	0.87	0.90	0.85

Graph Interpretation of Models

The figure below represents the evaluation metric graph used in a way that identifies the performance of different LLM models. They were tested based on BLEU, ROUGE-L, BERTScore, and QAG Score, which provide information about their efficiency in every aspect of text generation and comprehension.

The output of the four models for the performance comparison graph presented in Fig. 3 is as follows:

Gemma1.1-7B performed better than all models, with results of 0.90 in BLEU, 0.92 in ROUGE-L, 0.94 in BERT, and 0.91 in QAG. Its improved performance is a testament to its ability to generate high-quality, contextually rich, and fluent text as well as being coherent and accurate.

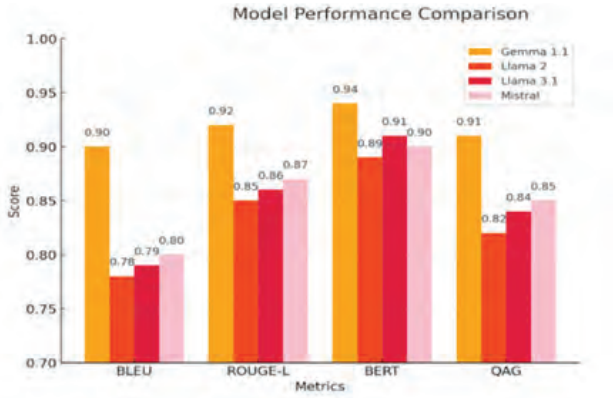

Fig. 3: Comparison of different models based on evaluation metrics

Llama2-7B bested 0.78 BLEU, 0.85 ROUGE-L, 0.89 BERT, and 0.82 QAG with great language modeling abilities but slightly lower coherence and fluency compared to Gemma 1.1. Still, it is a good enough choice for most NLP applications.

Llama3-8B improved over its predecessor to achieve BLEU score 0.79, ROUGE-L score 0.86, BERT score 0.91, and QAG score 0.84. This shows better comprehension of sentence formation and content preservation, a characteristic which makes it adequately qualified for application in highly contextual contexts.

Mistral-7B maintained competitive performance with 0.80 inBLEU, 0.87 in ROUGE-L, 0.90 in BERT, and 0.85 in QAG, which proves that it is proficient in natural language generation. But its slightly lower scores show certain restrictions in retaining fine-grained information while generating text.

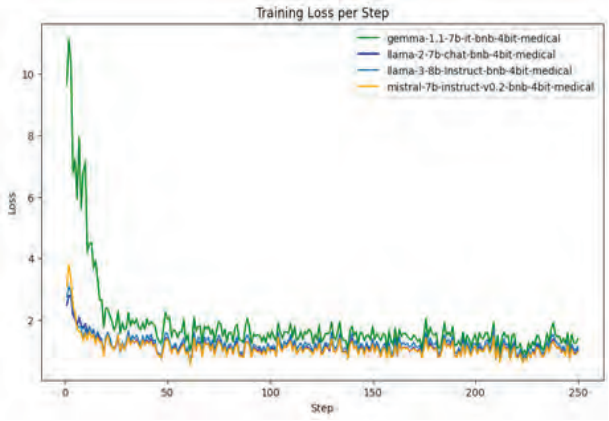

Fig. 4: Comparison of different models based on training loss per step

The above graph displays the training loss at each step of four models fine-tuned using QLoRA for clinical application with 4-bit quantization. Initially, all the models show high loss, and the maximum initial volatility is reported by Gemma1.1-7 B. However,as training progresses, the values of the loss stabilized in all models, and Mistral-7B and Llama3-8B recorded the lowest and most stable loss. The trend of convergence predicts that these models learn well for medical fine-tuning, with Gemma1.1-7B showing a bit more variance in the next steps. This comparison illustrates the stability and learning capability of each model during fine-tuning.

In summary, Gemma1.1-7B outperformed Llama2-7B, Llama3-8B, and Mistral-7B across all the measures taken, with the best BLEU, ROUGE-L, BERT, and QAG scores. Its better fluency, coherence, and contextual precision help it rank at the top. Though Llama3 had made some steps forward over Llama2, while Mistral ranked equally, both were slightly behind in remembering fine-grained facts.

Limitations of the Models

The boundaries of fine-tuned and guardrailled LLM with RAG largely include training bias, retrieval gaps, and answer limitations from guardrails. Though domain-specific adaptation through fine-tuning with LoRA is strengthened, it might fall short when presented with out-of-distribution requests or intricate medical situations beyond training coverage. Also, the use of vector search can lead to retrieval of the event of embeddings lacking sufficient granularity. Scalability and latency are also issues, primarily when working with big health datasets in real-time.

Comparative Evaluation of Guardrail Framework Performance

Table 2 compares the accuracy performance of three guardrail systems—Llama Guard, NVIDIA NeMo, and Guardrails AI—with a baseline model. The evaluation was conducted on a synthetic data set specifically designed to test edge-case situations, such as hallucination generation and attempts at jailbreak. The data set replicates real-world prompts that challenge the model's safety, factuality, and ethical response limits. This allows a comprehensive analysis of the guardrails' ability to improve the model's reliability in safety-critical domains.

Table 2: Accuracy Comparison of Guardrails Frameworks

Evaluation Aspect	Base Model (%)	Llama Guard (%)	Guardrails AI Model (%)	Break-Through(%
Hallucinations	5.0	2.8	1.5	3.2
Jailbreak Attemp	8.0	6.0	94.7	5.3

The results indicate that all three guardrails enhanced the accuracy of the model in avoiding hallucinations and jailbreaks to a large extent. Among them, Llama Guard achieved the maximum jailbreak prevention accuracy of 96.0%, and Guardrails AI was slightly better in hallucination prevention compared to others at 93.2%. These findings put emphasis on the effectiveness of adding systematic safety layers for boosting the reliability and robustness of language models in high-stakes medical use cases.

CONCLUSION

In conclusion, this study shows the effectiveness of using a combination of Guardrails, Retrieval-Augmented Generation (RAG), and fine-tuning to develop a context-sensing and reliable medical question system. The system enhances response accuracy without hallucinations through domain-specific fine-tuning, external knowledge retrieval, and safety measures. Of the models tested, the best was Gemma1.1-7B, which outperformed Llama2-7B, Llama3-8B, and Mistral-7B on a range of test metrics. The study highlights the importance of balancing model specialisation, retrieval efficiency, and safety to achieve peak performance in medical AI applications. Future studies can explore further enhancement of retrieval methods and real-time adaptability to make it more user-friendly and trustworthy.

REFERENCES

1. Rebedea, Traian, et al. "Nemo guardrails: A toolkit for controllable and safe llm applications with programmable rails." arXiv preprint arXiv:2310.10501 (2023), doi: 10.48550/arXiv.2310.10501.

2. Christophe, Clément, et al. "Med42-v2: A suite of clinical llms." arXiv preprint arXiv:2408.06142 (2024), doi:10.48550/arXiv.2408.06142.

3. Xu, P., et al. (2025). CHATQA 2: Bridging the gap to proprietary LLMs in long context and RAG capabilities. Proceedings of the ICLR 2025, doi: 10.48550/arXiv.2407.14482.

4. Ayyamperumal, Suriya Ganesh, and Limin Ge. "Current state of LLM Risks and AI Guardrails." arXiv preprint arXiv:2406.12934 (2024), doi: 10.48550/arXiv.2406.12934.

5. Gentner, Tobias, Timon Neitzel, Jacob Schulze, and Ricardo Buettner. "A Systematic Literature Review of Medical Chatbot Research from a Behavior Change Perspective." 2020 IEEE 44th Annual Computers, Software, and Applications Conference (COMPSAC), doi: 10.1109/COMPSAC48688.2020.0-172.

6. Gupta, Jahnvi, Vinay Singh, and Ish Kumar. "Florence – A Health Care Chatbot." 2021 7th International Conference on Advanced Computing & Communication Systems (ICACCS), doi: 10.1109/ICACCS51430.2021.9442006.

7. Vakayil, Sonia, D. Sujitha Juliet, Anitha J., and Sunil Vakayil. "RAG-Based LLM Chatbot Using Llama-2." Proceedings of the 2024 7th International Conference on Devices, Circuits and Systems (ICDCS), Coimbatore, India, April 23-24, 2024. IEEE, doi: 10.1109/ICDCS59278.2024.10561020.

8. Sanna, Leonardo, Patrizio Bellan, Simone Magnolini, Marina Segala, Saba Ghanbari Haez, Monica Consolandi, and Mauro Dragoni. "Building Certified Medical Chatbots: Overcoming Unstructured Data Limitations with Modular RAG." Proceedings of the International Conference on Medical Informatics, 2025.

9. Kirubakaran, Stewart S., Jasper Wilsie Kathrine G., Grace Mary Kanaga E., Mahimai Raja J., Ruban Gino Singh A., and Yuvaraajan E. "A RAG-based Medical Assistant Especially for Infectious Diseases." Proceedings of the 2024 International Conference on Inventive Computation Technologies (ICICT), Lalitpur, Nepal, April 24-26, 2024. IEEE, doi: 10.1109/ICICT60155.2024.10544639.

10. Bora, Arunabh, and Heriberto Cuayáhuitl. "Systematic Analysis of Retrieval-Augmented Generation-Based LLMs for Medical Chatbot Applications." Machine Learning and Knowledge Extraction, 6(4), 2355-2374, 2024. doi: 10.3390/make6040116.

Narrative Frames: AI-Driven Text-to-Video Synthesis

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ABSTRACT

Narrative Frame is a framework that utilizes AI to transform written stories into synchronized audiovisual narrations. Utilizing cutting-edge diffusion models for video generation and Google Text-to-Speech (gTTS) for narration, the framework produces short videos that visually and audibly portray each part of the input narrative. The most important innovation is its light-weight end-to-end pipeline, which integrates sentence tokenization, motion diffusion generation, automated voice-over, and subtitle alignment into a single process. In contrast to current tools, Narrative Frame prioritizes ease of use, with limited user input and rich narrative coherence through temporal synchronization of images and voice. This paper describes the design, deployment, and testing of the framework, coupled with real-world observations on usability, computational performance, and usefulness in digital storytelling, education, and content prototyping. Experimental evaluation confirms its ability to generate appealing story-consistent video clips with low latency and high perceived quality.

KEYWORDS *: Narrative frame, Text to video generation, Diffusion models, Text to speech, Deep learning, Story visualization, Multimodal content synthesis.*

INTRODUCTION

Deep learning and artificial intelligence have undergone significant advancements, creating phenomenally new do-mains, especially in the content generation focus on the creation of video from text description, which works wonders in improving narrative techniques.

This paper presents Narrative Frames, a state of the art text-to-video synthesis platform that employs Stable Diffu-sion Models to automatically generate corresponding videos for specified narratives. Unlike traditional story-telling which heavily depends on written texts or imagery, often referred to as text or image centric approach, there is always an embodied endeavor of making narratives more captivating. Recent advances in generative models like Stable Diffusion enable creation of images and videos that are not only visually appealing but also provide meaningful context to the text input.

The primary goal of Narrative Frames aims to accomplish automated video generation for stories that accompany existing narratives, thus changing the approach to video creation from the traditional technique of manual editing. This framework applies a diffusion model on the textual data to generate an image stack depicting the critical features of the narrative. In order to enrich the narrative served, Google Text-to-Speech (gTTS) is added to guarantee timing between narration and imagery to optimize engagement with the story.

Narrative Frames automates the creation of sophisticated videos using educational text, transforming them into personalized digital stories, automating the production process for holistic storytelling and multimedia experiences. This automation has implications for the education, digital media, and entertainment industries, as Narrative Frames caters to the emerging sophistication demand automation systems. Users simply provide their

stories, and the system handles the rest, dramatically streamlining the video production process. This is made possible by Narrative Frames' automated processes for turning text into video.

An emphasis on assessment focuses on the effectiveness and convenience in achieving high-quality, narrative-driven videos in terms of design, implementation, and challenges of the system.

RELATED WORK

Text-to-Image Generation

Most of the early efforts were plagued by having major issues with employing Generative Adversarial Networks (GANs) to generate images with a loose coherence to what was previously described in text form and ironing out the problems with the visual detail was dominating them nearly completely. They only produced a best guess output with only the very fundamental functionality being operational most of the time, with part of the aspects being somewhat in place. Some solutions that would fix some of these issues were: StackGAN, however, created a type of two step process with detail and resolution enhancement being added at each step after building the initial low detail version image from the text embeds. The procedure first produces a low resolution image from the input text and continuously refines it for greater fidelity in an attempt to create realism and contextuality.

Models such as Stable Diffusion have gained favor since they are able to add and remove noise in an iterative manner and generate high-quality images that are highly compatible with the input text.

Text-to-Video Generation

Text-to-video synthesis is a challenging task that encompasses transforming descriptive text input into visually pleasing and semantically consistent video output. One of the central challenges in the field is maintaining temporal coherence—smoothness and consistency of motion and scene change between successive frames—while faithfully representing the semantics of the input text. Early approaches such as MoCoGAN (Motion and Content Decomposed GAN) addressed this challenge by using GANs that model motion and content in a self-controlled, independent manner. This motion-content separation allowed for better control over dynamic and static aspects of video synthesis and led to higher realism and diversity in short video clips.

Recently, this field has been advanced further by the emergence of diffusion models. These models produce video clips by iteratively denoising random noise, refining it step by step into intelligible video frames. By enforcing temporal constraints and context-awareness at the time of denoising, diffusion-based models can create sequences with smoother transitions and higher visual realism. This methodology not only increases frame-to-frame coherence but also maintains the global narrative structure inferred from the text description, and thus the output videos are closer to the story intended.

Diffusion-based techniques overall are a paradigm shift towards text-to-video generation, achieving better performance in retaining semantic meaning as well as temporal dynamics compared to previous GAN-based approaches.

STABLE DIFFUSION MODEL PROCESS

The Stable Diffusion model is based on a two-step approach: a forward diffusion process and a reverse denoising process. Noisy observation x is progressively added to the original data x_0 step by step in a time sequence of steps T in the forward diffusion process. It can be mathematically represented as:

$$q(x_t \mid x_{t-1}) = \mathcal{N}(x_t; \sqrt{1-\beta_t} \cdot x_{t-1}, \beta_t \cdot \mathbf{I})$$

Where:

- x is noisy observation at time step t
- β is the variance schedule that determines the amount of noise to add at each step

In the reverse denoising process, the model learns to reverse each step to restore the original data using a neural network (typically U-Net). It estimates

$$p_\theta(x_{t-1} \mid x_t) = \mathcal{N}(x_{t-1}; \mu_\theta(x_t, t), \Sigma_\theta(x_t, t))$$

This enables the model to transform raw noise into real data conditioned on inputs such as text.

Noisy data at time t can be written as:

$$x_t = \sqrt{\alpha_t} \cdot x_{t-1} + \sqrt{1-\alpha_t} \cdot \epsilon$$

Where:

- x is the noisy observation at time t
- α is the noise schedule value at time t
- ε is Gaussian noise sampled from N(0, 1)

  α is chosen so that noise increases monotonically with time.

Reverse Denoising Process

During this phase, the neural network tries to learn the noise ε added. The aim is to bring the estimated noise as close as possible to the actual added noise in the forward process. The estimated noise is represented by ε'.

The loss function employed is:

$$\mathcal{L} = \mathbb{E}_{x_0,\epsilon,t}\left[\|\epsilon - \hat{\epsilon}_\theta(x_t, t)\|^2\right]$$

Where:

- $\hat{\varepsilon}_{theta}(x_t, t)$ is the predicted noise from the neural network
- θ are network parameters

The value denoised at time t-1 is then computed as:

$$x_{t-1} = \frac{1}{\sqrt{\alpha_t}}\left(x_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}}\hat{\epsilon}_\theta(x_t, t)\right) + \sqrt{\beta_t}\cdot z$$

Where

- β_t is the noise variance
- $z \sim \mathcal{N}(0, I)$ is Gaussian noise

Text-Guided Generation

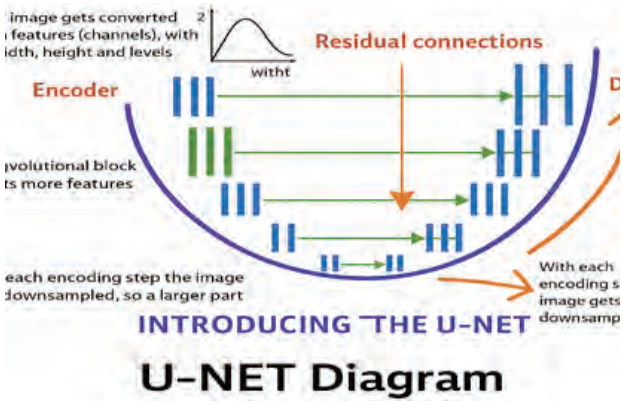

Fig. 1: U-NET Diagram

To guide image generation with text, a text encoder (like CLIP) is used to convert input text into embeddings. These embeddings are fed into the diffusion model so that the generation process produces visuals aligned with the description. This combination allows Stable Diffusion to generate detailed, realistic, and semantically correct images or videos as per the narrative input.

Operation of the Narrative Frames Project

The system "Narrative Frames" is designed to create videos from user-supplied stories in text format. It accomplishes this through Natural Language Processing (NLP), deep learning for text-to-image generation, voice synthesis, and video editing. This document explains the key components of the system.

Natural Language Processing (NLP)

NLP is used to process and analyze the input story. The first step is tokenization, where the story is split into individual sentences:

Story = {s1, s2, ..., sn}

Each sentence is processed independently. The system also detects the emotional tone (positive, negative, or neutral) of each sentence. This tone influences the visual style during image generation.

Named Entity Recognition (NER) is applied to extract key entities (characters, places, etc.). NLP tools like spaCy are used here. Then, deep learning models such as BERT are used to convert each sentence into numerical vectors (embeddings):

E = BERT(si)

These embeddings capture the meaning and are passed into the image-generation system.

Stable Diffusion Image Generation

Stable Diffusion is used to produce images from text embeddings. It is run in two stages:

Forward Diffusion: Applies noise to an image gradually until pure noise is reached.

$$x_t = \sqrt{\alpha_t}\cdot x_0 + \sqrt{1-\alpha_t}\cdot\epsilon$$

Reverse Denoising: Use a model to iteratively denoise to recover the image from noise.

$$x_{t-1} = \frac{1}{\sqrt{\alpha_t}}\left[x_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}} \cdot \epsilon_\theta(x_t, t)\right] + \sqrt{\beta_t} \cdot z$$

This process results in images that visually represent the input sentences.

Speech Synthesis Using gTTS

Google Text-to-Speech (gTTS) is used to convert each sentence into audio:

Ai=gTTS(si)

Where:

Ai : Audio output generated for the sentence sis_isi

si : Input sentence

gTTS: Google Text-to-Speech function used to convert text to speech

Video Assembly with MoviePy

Finally, MoviePy is used to combine images and audio into a single video. Images are shown in order, and audio is synchronized:

V = MoviePy({x1, x2, ..., xn}, {A1, A2, ..., Am})

Where:

- V = Final video
- xi = Images
- Ai = Audio clips

WORKING METHODOLOGY

The proposed system, Narrative Frames, is an AI-based end-to-end framework designed to convert narrative text into narrated video stories. It consists of five key stages: story segmentation, visual generation, audio narration, subtitle alignment, and final video merging.

1. Story Segmentation: The input narrative is cleaned and divided into semantic sentence-like units using SpaCy-based natural language processing. Pronouns are resolved to improve prompt clarity for later stages. These segments serve as independent prompts for video and audio generation.
2. Visual Generation: Each sentence is passed to AnimateDiff, a diffusion-based video synthesis model. AnimateDiff leverages CLIP embeddings for text conditioning and generates motion-consistent image frames. A checkpoint pretrained on 4-step inference is used to optimize speed and coherence. The resulting frames are converted into video clips using FFmpeg.
3. Audio Narration: Each sentence is synthesized into speech using a neural text-to-speech engine (e.g., Coqui TTS). The tool supports multiple pretrained voices. Each audio clip corresponds to one video segment, enabling precise alignment.
4. Subtitle Generation: Subtitles are auto-aligned using timestamps from audio synthesis. Sentence start times and durations are tracked, and text is overlaid using MoviePy to produce embedded subtitles synchronized with the narration.
5. Video Merging: All individual video clips and audio narrations are merged using MoviePy's video editor. This step ensures seamless playback with voice, visuals, and subtitles forming a coherent narrative.

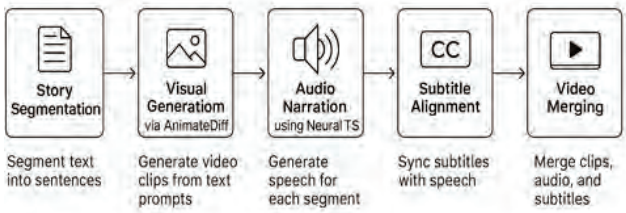

Fig. 2: Workflow Diagram of Narrative Frames System

The figure illustrates the complete working pipeline of the Narrative Frames system. It begins with Story Segmentation, where input text is divided into meaningful sentence units. These segments are then passed to the Visual Generation stage using AnimateDiff for video clip creation. Simultaneously, Audio Narration is produced for each segment using a neural TTS model. Subtitle Alignment synchronizes the narration with on-screen captions. Finally, Video Merging integrates all components—video clips, audio, and subtitles—into a unified, narrated video output.

ESTIMATING THE RELIABILITY OF STABLE DIFFUSION FOR TEXT-TO-VIDEO SYNTHESIS

Quantitative metrics and qualitative human evaluations are used in order to evaluate the stability and performance

of the Stable Diffusion model in generating text-to-video.

Evaluation Metrics

Fréchet Inception Distance (FID):

FID measures the resemblance between authentic and synthetic image frames. The lesser the FID score, the more authentic the produced images and the nearer they are to authentic image frames.

Video Consistency Score (VCS):

Measures how well individual video frames are aligned and coherent over time. This is crucial for avoiding flickering or sudden changes in generated videos.

Subjective Human Ratings:

Human evaluators rate the generated videos based on:

- Relevance to the input text
- Visual quality
- Temporal smoothness (frame-to-frame consistency)

Hardware Benchmark and Performance Evaluation

Stable Diffusion-based video generation was tested on a variety of GPUs to assess performance in terms of speed, memory consumption, and output quality.

Table 1:Performance and Quality Comparison

GPU Model	Avg. Generation Time (sec)	Avg. Memory Usage (GB)	FID Score ↓	VCS ↑	User Satisfaction (1–5)
NVIDIA GTX 1080 Ti	45.3	8.2	32.1	71.2	3.2
NVIDIA RTX 3060	34.7	9.4	27.8	78.6	3.9
NVIDIA RTX 4090	19.2	14.3	17.6	91.5	4.7
NVIDIA A100	11.5	18.7	13.2	94.1	4.9
VQGAN + CLIP (Legacy)	51.6	7.1	45.6	60.5	2.8

Observations

- Stable Diffusion with A100 delivers the best performance, producing high-quality, temporally smooth videos in the shortest time, with the lowest FID and highest user satisfaction.
- Consumer GPUs like the 1080 Ti struggle with speed and quality, often leading to less accurate or flickering outputs.
- Compared to legacy models like VQGAN + CLIP, Stable Diffusion achieves significantly lower FID scores, better coherence across frames, and greater satisfaction among human viewers.
- These benchmarks support the claim that Stable Diffusion, especially on high-end GPUs, is currently the most desirable framework for real-time or high-fidelity text-to-video synthesis.

CONCLUSION

The design and implementation of a Stable Diffusion model-based framework for text-to-video generation system was described in this study. This helps to transform text into action videos. The system is efficient in applying Natural Language Processing (NLP) by interpreting the provided text to analyze meanings and imagery description, and selecting semantics to image creation. An image's resemblance to its meaning is maintained because image generation is done using a stable diffusion model. All the images created are further merged with audio illustration to achieve seamless storytelling.

The Stable Diffusion model's incorporation in image synthesis is beneficial as it has the ability to create images at high resolution without straining the system's processing power. The model performs image synthesis using a forward noise diffusion and reverse denoising to create the images in line with the text provided. This ensures that the story is not altered. Context is expanded by the use of text embeddings which makes the system suitable for automated storytelling.

This study illustrates the possible outcomes of applying diffusion models to the generation of content based on textual descriptions which advances AI driven models.

This research contributes to the advancement of AI-

driven multimedia content generation by showcasing the potential of diffusion models in converting textual descriptions into visually engaging media. Future enhancements could explore improving the temporal continuity between generated frames, as well as integrating advanced speech synthesis techniques for enhanced auditory experiences. The findings underscore the promising intersection of NLP and diffusion-based models in creative AI applications, paving the way for further innovation in automated storytelling and content creation.

Abbreviations and Acronyms

- GAN: Generative Adversarial Network – A machine learning structure where two neural networks, the discriminator and the generator, are trained simultaneously to generate synthetic data that is extremely similar to actual data.
- NLP: Natural Language Processing – Subdivision of artificial intelligence that deals with human-computer linguistic communication, allowing machines to process, comprehend, and generate human language.
- FID: Fréchet Inception Distance – A measure employed to assess the quality of produced images by determining the difference in distribution between produced images and actual ones in a feature space.
- IS: Inception Score – A performance metric of generative models that estimates quality and diversity of the produced images through a pre-trained Inception model.
- T2V: Text-to-Video – A generative AI method that generates videos from natural language descriptions, allowing for automatic video generation based on text input.
- CNN: Convolutional Neural Network – A deep learning framework especially well-suited for processing grid-structured data like images, famous for its application of convolutional layers to identify patterns.
- RNN: Recurrent Neural Network – A form of neural network well-suited to sequential data, where nodes' connections constitute a directed graph along a temporal sequence, so information can endure.
- VQGAN: Vector Quantized Generative Adversarial Network – A form of GAN that merges vector quantization and adversarial training, allowing high-quality and intricate image synthesis.
- CLIP: Contrastive Language-Image Pretraining – An OpenAI model that is trained on visual concepts using natural language supervision, allowing it to comprehend images based on related text.
- SD: Stable Diffusion – A deep generative model based on a diffusion process for generating images from text inputs, renowned for creating high-quality, photorealistic images.
- Image Resolution (pixels): The resolution of processed or generated images is given in terms of pixel dimensions, e.g., 256×256 px or 512×512 px. This indicates the height and width of an image in pixels, which affects the detail level and quality directly.
- Computation Time (seconds or milliseconds): Time it takes to compute certain computations or model inferences is generally reported in seconds (s) or milliseconds (ms). Such measurements are used to assess the speed and responsiveness of models, especially in real-time or near-real-time use cases.
- Training Duration (epochs): The number of full passes over the entire training dataset is referred to as epochs. For instance, 50 epochs mean that the model has been trained on the entire dataset 50 times, which impacts both convergence and performance.
- GPU Memory Usage (gigabytes): The memory consumed by the GPU during training or inference is quantified in gigabytes (GB). The unit is important for establishing the scalability and viability of deep models on various hardware platforms.
- Computational Efficiency (FLOPS): Computational efficiency is measured in terms of FLOPS (Floating-Point Operations Per Second), which is a measure of how many arithmetic operations a model can execute per second. It is a standard used to compare the performance of models and hardware.

Equations

Fréchet InNXception Distance (FID)

$$\mathrm{FID} = \|\mu_r - \mu_g\|^2 + \mathrm{Tr}\left(\Sigma_r + \Sigma_g - 2(\Sigma_r\Sigma_g)^{\frac{1}{2}}\right)$$

where:

Inception Score (IS)

$$\mathrm{IS} = \exp\left(\mathbb{E}_x\left[D_{\mathrm{KL}}(p(y \mid x) \parallel p(y))\right]\right)$$

Where

- D_{KL}: Kullback–Leibler divergence
- $p(y \mid x)$: Conditional label distribution given an image :
- $p(y)$: Marginal distribution over all labels
- $\mathbb{E}_x$: Expectation over all generated images x

ACKNOWLEDGMENT

I deeply express my sincerest gratitude to my project guide, Dr. Pravin Shinde Sir, for his unselfish advice, regular encouragement, and constructive comments throughout the duration of this research. His expertise and experience played a significant role in defining the direction and outcome of this research.

I would also like to extend my gratitude to my lecturers and Shah and Anchor Kutchhi Engineering College Faculty of Artificial Intelligence and Data Science for the provision of the required resources and support that aided me in carrying out this research. The direction and motivation have significantly improved my learning experience.

Apart from that, I would also like to appreciate the work of my team members, who co-operated with one another and contributed constructively towards the project's success.

REFERENCE

1. Y. Liu et al., "AnimateDiff: Motion-Supervised Diffusion Models for Coherent Video Generation," arXiv preprint arXiv:2311.16459, Nov. 2023. https://arxiv.org/abs/2311.16459
2. B. Zhou et al., "VideoCrafter2: Overcoming Data and Computation Constraints for High-Quality Text-to-Video Generation," arXiv preprint arXiv:2401.12972, Jan. 2024. https://arxiv.org/abs/2401.12972
3. H. Kim et al., "SyncTalk: Synchronized Text-to-Speech with Lip-Accurate Talking Face Generation," IEEE Transactions on Multimedia, 2023. https://ieeexplore.ieee.org/document/10014351
4. Y. Chen et al., "T2VGen: High-Resolution Text-to-Video Synthesis with Latent Diffusion," CVPR 2023. https://openaccess.thecvf.com/content/CVPR2023/html/Chen_T2VGen_High-Resolution_Text-to-Video_Synthesis_with_Latent_Diffusion_CVPR_2023_paper.html
5. T. Li et al., "Make-A-Video3D: Learning a Generative Video Diffusion Model from Multi-View Images," arXiv preprint arXiv:2310.01296, 2023. https://arxiv.org/abs/2310.01296
6. Y. Zhang, H. Sun, and A. Zhao, "End-to-End Text-to-Image Synthesis with Deep Convolutional Networks," IEEE Transactions on Neural Networks and Learning Systems, vol. 32, no. 12, pp. 5042–5053, Dec. 2021. https://doi.org/10.1109/TNNLS.2021.3054768
7. Y. Li, H. Qi, and Z. Wang, "Video-to-Text Description Generation Using a Multimodal Transformer," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 44, no. 9, pp. 4820–4835, 2022. https://doi.org/10.1109/TPAMI.2021.3056312
8. R. Ramesh et al., "Zero-Shot Text-to-Image Generation," Proceedings of the International Conference on Machine Learning (ICML), vol. 139, pp. 8821–8831, 2021. https://proceedings.mlr.press/v139/ramesh21a.html
9. A. Gupta, Y. Choi, and P. Wang, "Text2Video: Text-driven Video Generation," Proceedings of the AAAI Conference on Artificial Intelligence, vol. 35, no. 7, pp. 5565–5572, May 2021. https://ojs.aaai.org/index.php/AAAI/article/view/1680
10. P. Zhang, S. Liu, H. Zhao, and J. Tang, "Enhancing Text-to-Image Synthesis with Multimodal Sequential Learning," IEEE International Conference on Multimedia and Expo (ICME), pp. 235–240, July 2020. https://ieeexplore.ieee.org/document/9102974

Evaluating the Performance of Causal Inference Techniques in Treatment Effect Estimation

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ABSTRACT

The application of Machine Learning (ML) in medicine has gone a long way to improve diagnosis quality and treatment through data-based decision-making. Conventional methods of ML have traditionally centered on prediction, not usually being capable of revealing cause-and-effect relations crucial for good healthcare interventions. The effectiveness of causal inference methodologies is studied in this paper using the Infant Health and Development Program (IHDP) data—a semi-synthetic dataset with known treatment effects—allowing to naturally measure how accurately causal estimators can fit. Four methods of causal inference that are better known were tried: Propensity Score Matching (PSM), Inverse Probability Weighting (IPW), Doubly Robust estimation (DR), and Causal Forests. These approaches were contrasted using primary performance measures such as Average Treatment Effect (ATE), Root Mean Square Error (RMSE), variance, and bias. The findings showed that neither IPW nor PSM had much bias and both estimates were consistent with the lowest RMSE pertaining to PSM (3.6476) exhibiting the best predictive reliability. DR exhibited even better reduction in bias (0.9638) but experienced higher variance from sensitivity to subject variability. Causal Forests also successfully modeled heterogeneity of treatment effects, albeit with slightly higher bias (1.5377) and RMSE (3.7804). The results highlight that the selection of causal inference method must be congruent with the objectives of analysis—minimizing bias, variance control, or detecting heterogeneous effects. Finally, the research emphasizes the role of causal inference to enhance both robustness and interpretability within the context of ML-based models in healthcare.

***KEYWORDS** : Causal forest, Causal inference, Causal inference techniques, IHDP dataset, Machine learning, Treatment effect.*

INTRODUCTION

Health care is a rapidly changing industry. New technologies and data-driven insights are substantially changing patient care to the benefit of the medical professionals, who can now use innovative technologies and new data to help improve patient care, thus resulting in the enhanced patient experience. Machine Learning (ML) has had a significant impact on healthcare due to its capability to provide powerful data-driven predictions thus improving diagnostics and enabling better patient risk stratification [1]. While traditional machine learning excels at prediction, it does not explain the underlying cause-effect relationship which plays a crucial role in healthcare [2]. This is where the concept of causal inference becomes essential. Using Causal Inference helps understand the cause and effect relationships in data by addressing assumptions, confounding factors and noncompliance in data [3]. As mentioned in [4], the primary objective of causal inference is to expand Machine Learning capabilities beyond prediction to intervention and decision-making, where fairness and model stability problems arise. Given capital and ethical limitations, randomized experiments are not always viable to answer all causal questions [5], making observational data a vital and cost-effective alternative for estimating causal effects [6]. The IHDP dataset was used to assess causal inference techniques. The IHDP dataset is a semi-synthetic dataset based on randomized study of specialist visits and their impact on children's cognitive development [7].IHDP dataset

provides ground truth treatment effects which makes it possible to determine the difference between the estimated and real outcomes thus making the dataset an outstanding reference model for the assessment of causal inference methods. Causal inference methods were applied to the IHDP dataset to enhance model reliability, handle treatment effect heterogeneity, and provide more robust causal insights.

Further, this paper is structured as follows: Section II provides a detailed literature survey, highlighting previous work and key findings related to Causal Inference in healthcare. Section III describes the methodology and an exploration of various models that have been implemented, including details about the dataset. Section IV presents the results based on evaluation parameters, while Section V summarizes key findings.

LITERATURE ANALYSIS

This section offers a thorough review of current research on causal inference methods. Causal inference has been an essential component of observational studies in various areas of healthcare, economics, and public policy During the former attempts to estimate treatment effects in the absence of randomized controlled trials, Rosenbaum and Rubin [8] introduced PSM, with the aim of balancing covariates across control and treatment groups to approach confounding. The technique provided the foundation, allowing matching with a scalar score rather than high-dimensional covariates, and has since been used extensively in medical and behavioral sciences [9].

Following PSM, scholars introduced Inverse Probability Weighting (IPW) to address cases of weak matches or overlap. IPW, through reweighting the units by the inverse of treatment assignment probability, creates an artificial sample that mimics a randomized trial [10]. Researches [11] demonstrated IPW's capacity to control confounding but also demonstrated its susceptibility to inflation of variance, particularly in the presence of high propensity scores.

To improve estimation stability, Doubly Robust (DR) Estimation methods were proposed, which employed a propensity model and an outcome regression model. The approach, detailed in [12], yields consistent estimates if one of the two models is correctly specified. Comparative studies, for example, those by Ridgeway et al. [13], have confirmed that DR estimators perform better than either PSM or IPW alone with respect to bias-variance tradeoff.

With advancements in machine learning, non-parametric methods such as Causal Forests are being recognized more widely in terms of estimating heterogeneous treatment effects. Based on the generalized random forest algorithm, causal forests recursively split the data to incorporate complicated interactions as well as effect modification [14].

The Infant Health and Development Program (IHDP) dataset, [15], has also become the standard against which to measure causal inference techniques under realistic confounding. As a semi-simulated dataset with known treatment effects, IHDP allows for objective comparisons of methods such as PSM, IPW, Doubly Robust Estimation (DR), and Causal Forests [16].

Performance metrics like Average Treatment Effect (ATE), bias, variance, and Root Mean Squared Error (RMSE) have been used throughout literature to compare method performance. For example, [17] offered a systematic simulation-based comparison of PSM, IPW, and DR, noting the trade-offs with respect to estimator precision and model misspecification sensitivity. In more recent work, techniques incorporating machine learning for propensity estimation or outcome modeling, e.g., generalized boosted models and neural networks, have shown better accuracy on measures such as RMSE and bias reduction [18].

In general, the history of causal inference methods is moving away from purely statistical to hybrid and machine learning-based methods. Although the older methods such as PSM and IPW set the foundation, newer methods such as DR and causal forests are major improvements, with enhanced generalizability and performance on challenging observational data.

METHODOLOGY

This section will cover and explain the description of the dataset, the preprocessing steps, and the techniques for conducting causal inference on the dataset.

Dataset Description

The dataset used in this paper was collected from the IEEE DataPort repository that was created to benchmark their treatment effect estimation methods. The dataset is based on the randomized controlled experiment carried out by the Infant Health and Development Program [2], which target low-birthweight and preterm infants. In this study, the dataset is semi-synthetic in design based on actual observational data and includes both factual and counterfactual outcomes, which allows direct estimation and evaluation of causal inference methods.

The dataset is composed of the following:

Covariates - A complete list of demographics, socio-economic and health-related characteristics (ex., income, birth weight, parental education level, the safety of the neighborhood).

Treatment Assignment - A binary treatment variable encoded to inform if he/she has received a treatment/ intervention.

Outcomes - These include the observed factual outcomes (outcome_factual) and simulated counterfactual outcomes (outcome_counterfactual) as well as ground truth potential outcomes (mu0, mu1) for the evaluation of the simulated data.

Data Preprocessing

The data quality and consistency were established with the use of the data pre-processing in the following ways:

a. Null values and duplicates: Every row was assessed for null values and were handled appropriately so that modelling could be performed without diminishing the quality of the data.

b. Variable type: Categorical and numerical variables were assessed and corrected to typecast prior to exposure to causal models.

c. Normalization: Continuous variables were normalized to make the mean zero and standard deviation one to help with speed of convergence during model training.

d. Variable scaling: Significant features were scaled using standard variable scaling to minimize the influence of any one variable or factor.

e. Dataset splits: The original dataset was separated so that a training and testing set were created to extract generalization of the causal model (80-20 is the model used).

f. Covariate selection: Treatment, Y outcome, and X covariates were explicitly defined in relationship to domain knowledge and potential relationship impact to assure causation learning.

Causal Models

Propensity Score Matching (PSM)

PSM estimates treatment effect by matching treated and untreated units by their propensity scores, which are the predicted probabilities of receiving treatment given covariates. Matching methods are commonly used to infer causal effects using data from observational studies. Such methods outline how to turn the original dataset into a matched dataset in which the distribution of confounders is appropriately balanced across treatment groups [19].

Inverse Probability Weighting (IPW)

IPW uses an estimate of the probability of receiving treatment to weight each unit by the inverse of that probability [20]. This allows for a balanced estimation between treated and control groups. The ATE is estimated in equation (1), where T is the treatment, Y is the outcome, and e(X) is the propensity score.

$$IPW = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{T_i Y_i}{e(X_i)} - \frac{(1-T_i)Y_i}{1-e(X_i)}\right) \quad (1)$$

IPW was selected because it was simple, and provided a model to reduce confounding based on the treatment model.

Doubly Robust Estimates

A doubly robust estimation is a method that combines IPW and an outcome model. It provides accurate estimation if either of the two models is correctly specified [21]. The estimator is provided in equation (2), where μ1 and μ0 are predicted (i.e., outcome) scores and e(X) is the propensity score.

$$DR = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{T_i - e(X_i)}{e(X_i)(1-e(X_i))}(Y_i - \mu_{T_i}) + \mu_1(X_i) - \mu_0(X_i)\right] \quad (2)$$

DR estimation was chosen because it is doubly robust, and can be obtained with misspecification of either the treatment or outcome models.

Causal Forest

Causal Forest is a tree-based approach for estimating treatment effects for individuals using data partition learning [22]. It estimates the Conditional Average Treatment Effect (CATE) shown in equation (3), where X are covariates.

$$\tau^x = E[Y(1) - Y(0) \mid X = x] \quad (3)$$

Causal Forest was chosen because it is flexible in estimating non-linear relationships and treatment effect heterogeneity.

RESULTS AND DISCUSSION

This section shares the principal findings from the experimental analysis evaluating treatment effects through the lens of causal inference. The evaluation has highlighted differences across several evaluation dimensions including estimation accuracy, consistency and robustness.

Evaluation Parameters

Similar to supervised machine learning models, causal inference techniques also have corresponding evaluation metrics that capture the quality of treatment effect estimation. The four base evaluation metrics used in this study were Average Treatment Effect (ATE), Root Mean Squared Error (RMSE), Bias, and Variance. ATE estimates the average difference in the chosen outcome between the treatment group and control group (4) and RMSE (5) measures total estimation error by providing fairly greater penalties for larger deviations and gives a measure of accuracy for predicted effects. Bias (6) provides a summary of the extent to which method overestimated or under-estimated ATE. Variance (7) identifies the degree of sensitivity of an estimation approach to the total variability within the data, this reflects both reliability and stability across samples. The combination of metrics provides some consistency and stability along with measures of accuracy (low RMSE), reliability (low Bias) and robustness (low Variance) through the realm of treatment effect estimation.

$$ATE = E[Y(1)] - E[Y(0)] \quad (4)$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \quad (5)$$

$$Bias(\hat{Y}) = E(\hat{Y}) - Y \quad (6)$$

$$Variance = E[(\hat{Y} - E[\hat{Y}])^2] \quad (7)$$

Classification Results

A comparative assessment of various causal inference methods including PSM, IPW, DR, and CF was completed across all of the major performance indicators: ATE, bias, RMSE, and variance. The analyses were performed on the IHDP benchmark data on both the training and testing sets.

As indicated in Table 1, for training, PSM and IPW were nearly equivalent with respect to ATE and RMSE, although PSM showed slightly better bias (1.5608 vs. 1.5467). The DR method again did best with the lowest training bias (1.4801), albeit with higher variance. Causal Forest had the lowest RMSE of all models (3.7775), but higher training bias (1.4596) and variance.

Likewise, on the test dataset, the DR method again had the lowest ATE bias (0.9638) and a competitive RMSE (3.7473) indicating accurate and stable treatment effect estimation. PSM also performed well because it had a low RMSE (3.6476) and a relatively lower test bias (0.9864), conveying its solid performance despite its more simplistic nature. IPW was in the middle of all performance measures. The Causal Forest performed the best in terms of modeling power; it did exhibit the highest test bias (1.5377) and the highest ATE (4.2304). These measures suggest it was overfitting or sensitive to variance in the data relative to all other measures in this situation, as shown in Table 2.

Table 1. Training Data Performance Metrics

Method	ATE	RMSE	Bias	Variance
PSM	4.0581	3.8469	1.5608	7.8886
IPW	4.0440	3.8412	1.5467	0.0000
Doubly Robust	3.9775	4.0482	1.4801	3.5407
Causal Forest	3.9569	3.7775	1.4596	2.5659

Table 2. Testing Data Performance Metrics

Method	ATE	RMSE	Bias	Variance
PSM	3.6791	3.6476	0.9864	0.0000
IPW	3.7732	3.6742	1.0805	1.9721
Doubly Robust	3.6565	3.7473	0.9638	2.7524
Causal Forest	4.2304	3.7804	1.5377	9.51

Figure 1 and 2 provide a more refined view of model performance of training and testing data with heatmaps for ATE, Bias, RMSE, and Variance for the four approaches. By comparison, it reaffirms that DR had a lower amount of bias but very high variance, and PSM improved on both bias and RMSE in either setting and across both datasets. Causal Forest was not consistent and has presented high variance and error metrics for ATE that we observed on the test dataset earlier.

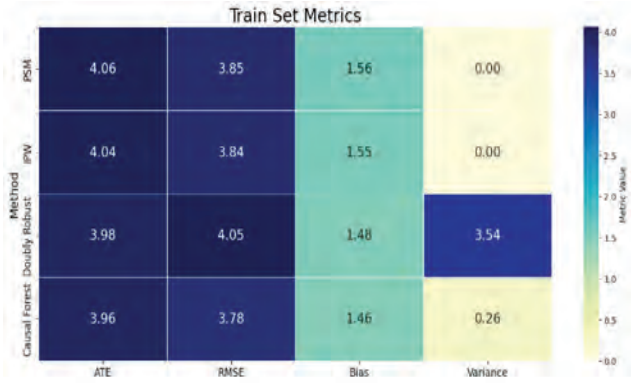

Fig. 1: Heatmaps of performance metrics (ATE, Bias, RMSE, Variance) for all methods on training dataset

Fig. 2: Heatmaps of performance metrics (ATE, Bias, RMSE, Variance) for all methods on testing dataset

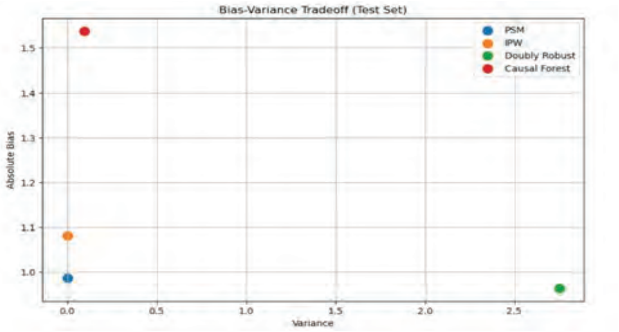

Fig. 3: Bias-Variance Tradeoff on the test set across all causal inference methods.

Figure 3 shows the bias-variance tradeoff for all methods on the test set which allows us to better understand the tradeoff between model complexity and estimation accuracy. PSM and IPW both fall in the low bias, low variance, bottom-left quadrant, while DR has the lowest bias but very high variance. CF falls into the top-left quadrant, implying not only higher bias, but significantly higher bias while still possessing some mild amount of variance. This is an indication of lack of robustness.

CONCLUSION

Causal inference methods were reviewed on the IHDP data set using key metrics such as Average Treatment Effect, Root Mean Square Error, bias, and variance. In the study we compared four commonly used causal inference approaches namely propensity score matching, inverse probability weighting, Doubly Robust estimation, and causal forests. Among these methods, PSM and IPW were the appropriate methods for case scenarios exhibiting stable and low bias causal estimates with near zero variance when treatment effects were uniform. PSM further achieved the lowest test RMSE (3.6476) which indicates a strong predictive performance. The Doubly Robust approach minimized bias (0.9638) more effectively than the other methods; however, it was sensitive to the subject variability present in the sample, eventually leading to higher variance. The treatment effect heterogeneity was best estimated by Causal Forest, reflecting its strength in modeling complex relationships, though it showed slightly higher bias (1.5377) and RMSE score (3.7804) compared to other methods. These findings demonstrate that every approach has distinct benefits, and the optimal choice

depends on whether capturing heterogeneous effects, variance control, or bias reduction is the top priority. In summary, the best analysis approach is the one that fits the goals of the analysis and the features of the data.

REFERENCES

1. Adeniran, I.A., Efunniyi, C.P., Osundare, O.S. and Abhulimen, A.O., 2024. Data-driven decision-making in healthcare: Improving patient outcomes through predictive modeling. Engineering Science & Technology Journal, 5(8).
2. Zhang, W., Ramezani, R. and Naeim, A., 2022. Causal inference in medicine and in health policy: A summary. In HANDBOOK ON COMPUTER LEARNING AND INTELLIGENCE: Volume 2: Deep Learning, Intelligent Control and Evolutionary Computation (pp. 263-302).
3. Pearl, J., 2001. Causal inference in the health sciences: a conceptual introduction. Health services and outcomes research methodology, 2, pp.189-220.
4. Cui, P. and Athey, S., 2022. Stable learning establishes some common ground between causal inference and machine learning. Nature Machine Intelligence, 4(2), pp.110-115.
5. Dahabreh, I.J. and Bibbins-Domingo, K., 2024. Causal inference about the effects of interventions from observational studies in medical journals. Jama, 331(21), pp.1845-1853.
6. Yao, L., Chu, Z., Li, S., Li, Y., Gao, J. and Zhang, A., 2021. A survey on causal inference. ACM Transactions on Knowledge Discovery from Data (TKDD), 15(5), pp.1-46.
7. Sheth, P., Jeong, U., Guo, R., Liu, H. and Candan, K.S., 2021, October. CauseBox: A Causal Inference Toolbox for BenchmarkingTreatment Effect Estimators with Machine Learning Methods. In Proceedings of the 30th ACM International Conference on Information & Knowledge Management (pp. 4789-4793).
8. Rosenbaum, P.R. and Rubin, D.B., 2023. Propensity scores in the design of observational studies for causal effects. Biometrika, 110(1), pp.1-13.
9. Wyss, R., Yanover, C., El-Hay, T., Bennett, D., Platt, R.W., Zullo, A.R., Sari, G., Wen, X., Ye, Y., Yuan, H. and Gokhale, M., 2022. Machine learning for improving high-dimensional proxy confounder adjustment in healthcare database studies: An overview of the current literature. Pharmacoepidemiology and drug safety, 31(9), pp.932-943.
10. Matsouaka, R.A., Liu, Y. and Zhou, Y., 2024. Overlap, matching, or entropy weights: what are we weighting for?. Communications in Statistics-Simulation and Computation, pp.1-20.
11. Shiba, K. and Kawahara, T., 2021. Using propensity scores for causal inference: pitfalls and tips. Journal of epidemiology, 31(8), pp.457-463.
12. Evans, K., Sun, B., Robins, J. and Tchetgen, E.J.T., 2021. Doubly robust regression analysis for data fusion. Statistica Sinica, 31(3), pp.1285-1307.
13. Ridgeway, G., McCaffrey, D.F., Morral, A.R., Cefalu, M., Burgette, L.F., Pane, J.D. and Griffin, B.A., 2022. Toolkit for weighting and analysis of nonequivalent groups: a tutorial for the R TWANG package. Santa Monica, Calif: Rand.
14. Li, L., Levine, R.A. and Fan, J., 2022. Causal effect random forest of interaction trees for learning individualized treatment regimes with multiple treatments in observational studies. Stat, 11(1), p.e457.
15. Ruth, T., 2024. Infant health and development program (ihdp): Enhancing the outcomes of low birth weight, premature infants in the united states, 1985-1988.
16. Dadi, A.F., Miller, E.R., Woodman, R.J., Azale, T. and Mwanri, L., 2021. Effect of perinatal depression on risk of adverse infant health outcomes in mother-infant dyads in Gondar town: a causal analysis. BMC Pregnancy and Childbirth, 21, pp.1-11.
17. Steurer, M., Hill, R.J. and Pfeifer, N., 2021. Metrics for evaluating the performance of machine learning based automated valuation models. Journal of Property Research, 38(2), pp.99-129.
18. Collier, Z.K., Leite, W.L. and Zhang, H., 2023. Estimating propensity scores using neural networks and traditional methods: a comparative simulation study. Communications in Statistics-Simulation and Computation, 52(9), pp.4545-4560.
19. Ulloa-Pérez, E., Carone, M. and Luedtke, A., 2024. Propensity score augmentation in matching-based estimation of causal effects. arXiv preprint arXiv:2409.19230.
20. Chesnaye, Nicholas C., et al. "An introduction to inverse probability of treatment weighting in observational research." Clinical kidney journal 15.1 (2022): 14-20.
21. Kennedy, Edward H. "Towards optimal doubly robust estimation of heterogeneous causal effects." Electronic Journal of Statistics 17.2 (2023): 3008-3049.
22. Venkatasubramaniam, Ashwini, et al. "Comparison of causal forest and regression-based approaches to evaluate treatment effect heterogeneity: an application for type 2 diabetes precision medicine." BMC Medical Informatics and Decision Making 23.1 (2023)

A Data-Driven Forecast of Indian Elections Using Twitter Sentiment Analysis

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ABSTRACT

In this digital age, tweets serve as powerful reflections of public mood, making sentiment analysis an essential tool for interpreting social dynamics. An important political event, the 2019 Indian Lok Sabha elections attracted a lot of public attention and sparked a lot of discussion on social media sites like Twitter (now X) etc. Sentiment analysis of these tweets offers important information about the sentiment of voters and a general opinion regarding leaders and political parties. Twitter is a great data source for electoral forecasting since it is a microblogging platform that allows people to express their ideas, opinions and attitudes in real time. Capturing a text's emotional tone is a crucial problem in sentiment analysis using Natural language processing. This study offers a thorough approach to Twitter sentiment analysis using models like CNN, BERT and some other machine learning techniques. This research performs sentiment analysis using a large dataset of tweets collected during the 2019 Lok Sabha elections. The results show how effective deep learning models—in particular, CNNs—are in predicting sentiment with high accuracy (up to 94.72%).

***KEYWORDS** : CNN, Elections, Sentiment analysis, Tweets, Twitter.*

INTRODUCTION

Sentiment analysis is considered a crucial part of Natural Language Processing (NLP), it takes into account the identification and classification of the sentiment expressed in the textual data, it helps improve data with useful insights to support better decisions in different fields. The field of sentiment analysis application is broad and covers multiple areas such as business customer feedback and the state of opinions on social, economic, political, and cultural aspects of a country. The method of sentiment analysis is now one of the main sources for election forecasting in the digital era. With the increase in social media sites like Twitter electorates can express their thoughts, preferences as well as criticize the parties in power and their candidates. By collecting this random data, researchers can get to know the voter's feelings, which allow them to make correct prediction regarding the elections. This method has proved to be efficient in forecasting, monitoring the evolving public opinion as well as in the campaign's political dynamics and has thus enhanced the prediction of voting trends. This study focuses on the sentiment analysis of the Indian Lok Sabha elections of 2019. The data include Tweets on the two major political parties: 29,930 tweets on Indian National Congress (INC) and 47,766 tweets on Bhartiya Janata Party (BJP). These statistics are an interesting source for scientific research, since they represent a variety of viewpoints and emotions of the voters throughout the election campaign. Once the data was collected, it was processed and evaluated using multiple sentiment analysis algorithms to extract and interpret underlying emotional patterns. These include techniques such as CNN and Bi-directional Encoder Representations from Transformers (BERT), as well as Linear Support Vector Classifier (SVC) that run Term Frequency–Inverse Document Frequency (TF-IDF). The findings demonstrate the growing significance of social media as a source of data and the effectiveness of advanced Natural Language Processing methods in political forecasting.

This study aims to demonstrate effectiveness of advanced Natural Language Processing methods in political forecasting. With increasing digitalization sentiment analysis provides a real-time and scalable approach for understanding public opinion. By analyzing large amount of unstructured data, deeper insights into voter inclination and emerging trends can be obtained. As AI technology continues to advance, sentiment analysis will play an increasingly vital role in political research, campaign strategy, and governance, making it an indispensable tool in the digital age.

LITERATURE REVIEW

It is very important to have an overview of public opinion, especially during major events like elections. Sentiment analysis is a very powerful technique that can help in elections by providing insights into public opinion, enabling political strategies to align with voter sentiment. With an increasing use of social media platforms like Twitter where various topics are discussed amongst the people using it, real time sentiment analysis has become a vital method for studying the thought process of the society. Tweets are a major source of data for sentiment analysis. Computer based sentiment analysis became popular only after subjective texts became available on the web. As a result, 99% related research papers were published after 2004.

There are four major methods of sentiment analysis (traditional approaches, machine learning, deep learning, and hybrid methods). Older approaches like lexicon-based methods are simple and easy to understand but struggle with complex language features such as sarcasm or mixed languages. Similarly traditional machine learning methods rely on manually created features, making them less useful for handling unstructured text data.

Recent advancements in AI, particularly in the deep learning approaches like CNN have transformed sentiment analysis by enabling automatic detection of patterns and understanding context better. CNN is very good at capturing word and phrase combinations (n-grams), making it highly effective for tasks like sentiment classification.

Most studies on election opinion mining have relied on conventional machine learning methods. Previous studies have reported a maximum accuracy of 86.3% using a decision tree model with TF-IDF text representation [1]. However, these machine learning approaches often struggle to capture the complex and slightly different languages used in political discussions, limiting their effectiveness in capturing sentiments.

Despite the growing interest in election sentiment analysis, very few researchers have focused on using CNN for Indian elections. A significant challenge in analyzing Indian tweets is the use of regional languages, making the task more complex [2]. Preprocessing plays an important role in handling tweets involving steps like removing URLs, extra spaces and special characters, performing spelling corrections and tokenization. The widely used Natural Language Tool-Kit (NLTK) library has been used for preprocessing. While traditional machine learning approaches have been commonly used, deep learning techniques consistently achieved higher accuracy. By capitalizing on the strengths of Machine Learning (ML) and Deep learning (DL) approaches, hybrid models can overcome their own individual limitations, leading to more accurate and computationally efficient solutions.

This study aims to reduce the gaps in election sentiment analysis by using a CNN model to classify sentiment in tweets from the 2019 Lok Sabha election. However, challenges like misinterpreting sarcasm, irony, and humor can lead to incorrect sentiment classification. The goal is to enhance sentiment analysis accuracy, helping political campaigns and addressing misinformation and biased elections.

DATA COLLECTION

This research analyzes tweets from the "Indian Election Tweets (2019)" dataset available on Kaggle [3]. The dataset contains a total of 78,760 tweets, which are further split between two major political parties in India: 48,766 tweets for Bhartiya Janata Party (BJP) and 29,930 tweets for Indian National congress (INC)

The dataset used was generated by using Twitter Application Programming Interface (API) and scraping libraries from Github. The dataset consists of two labels: positive (1) and negative (0), these labels are assigned by analyzing the tweets and categorizing them in the mentioned categories using Valence Aware Dictionary and sentiment Reasoner (VADER) tool.

It is essential that the dataset is balanced to prevent any bias generated in the model. The dataset used represents this balance with respect to the ratio of positive to negative tweets of a party. Using tweets collected during the Lok Sabha elections of 2019, the generated model is expected to provide an unbiased and accurate representation of sentiments expressed by users.

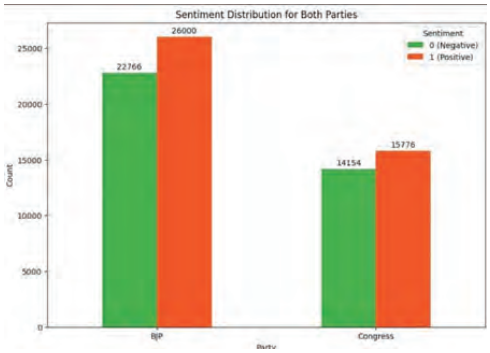

Fig. 1 Sentiment distribution for BJP and Congress tweets (2019 Lok Sabha election)

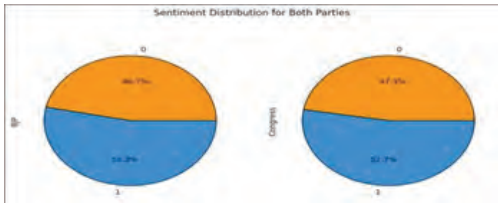

Fig. 2 Sentiment distribution for BJP and Congress tweets (2019 Lok Sabha election).

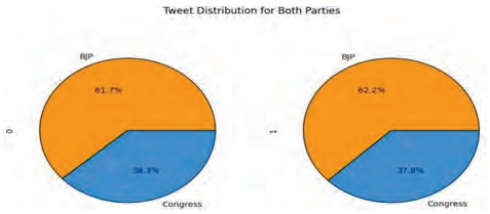

Fig. 3 Sentiment distribution for BJP and Congress tweets (2019 Lok Sabha election).

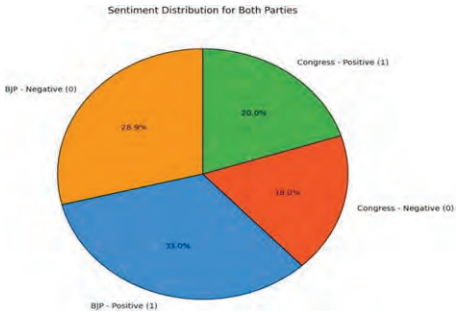

Fig. 4 Sentiment distribution for BJP and Congress tweets (2019 Lok Sabha election).

DATA PREPROCESSING

The data preprocessing was done in multiple steps to ensure that data is clean and consistent before training the sentiment analysis model. The main goal was to refine the text and balance the dataset to prevent any biases in the model's prediction.

The dataset included tweets from two prime political parties which are namely Indian National Congress (INC) and Bharatiya Janata Party (BJP). Since the source had two datasets, each was processed separately before being combined. The major steps involved were:

Loading Data: The datasets were loaded from CSV files, and unwanted columns were removed.

Duplicate Removal: Identical tweets within each dataset were removed to make sure the model does not overfit.

Text Cleaning: A preprocessing function was applied to the tweets to remove noise and normalize the text.

To standardize the data a preprocessing function was implemented. The following steps were applied:

Removal of URLs: Any hyperlinks starting with 'http', 'https' or 'www' were removed to eliminate unnecessary external references.

Elimination of Mentions and Hashtags: Twitter mentions using '@' and hashtags (#) were removed to highlight the tweet content better.

Digit Removal: Numbers were eliminated to prevent any numerical bias.

Punctuation Removal: Non alphanumeric characters were discarded to maintain textual consistency.

Lowercasing: The text was converted to lowercase to ensure consistency and avoid duplication due to case differences.

The preprocessing function applied these transformations to every tweet before further processing.

To ensure that the model does not develop bias toward any sentiment class, the dataset was balanced:

The dataset contained two classes: positive (target=1) and negative (target=0).

The smaller class was resampled using the resample function from a Scikitlearn (sklearn) module to match the size of the larger class.

The balanced dataset was then used for training, to improve model generalization and fairness.

By performing these preprocessing steps, the dataset was made more suitable for sentiment classification, ensuring high quality input for the neural network model.

PROPOSED METHODOLOGY

CNN can be effectively used for NLP tasks due to its capability to extract and analyze spatial features from texts. Unlike Recurrent Neural Network (RNN), which process text sequentially, CNN identifies sentiment related features through local feature extraction using convolutional filters. Before the text data is fed into the CNN model, it undergoes some important preprocessing steps to standardize and enhance the ability of the model to learn meaningful patterns. The preprocessing steps are tokenization along with padding and truncation. The process of conversion of raw text into words or sub-words, where each word is assigned a unique integer identifier, creating a numerical representation of the text is known as tokenization. Since neural networks require a fixed length of inputs, sequences are padded (by adding extra 0s) or truncated (removing extra words) to ensure uniform length.

The model is made up of mainly seven types of layers, out of which the first layer used is the embedding layer which converts the input textual data into dense vector representations which help capture the semantic relationship between words. Followed by the embedding layer we have our convolutional layer which helps in detecting patterns in data using filters. The third type of layer is the pooling layer which minimizes the spatial difference of feature maps at the same time preserving the necessary information. It also reduces computational complexity and chance of overfitting. The next layer is batch normalization layer which normalizes the activations to stabilize training and improve performance. The flatten layer converts the multidimensional inputs into a 1D vector which will be used in fully connected layers.

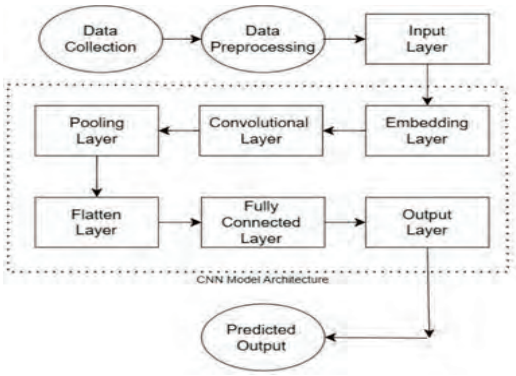

Fig. 5. CNN model general architecture

"BERT is a deep learning model made to understand the context of words in a sentence by analyzing both right and left surroundings" [5]. It is pre-trained on vast amounts of unlabeled text data and can be fine-tuned for several NLP tasks, including sentiment analysis.

The pre-processed data was tokenized using a transformer-based tokenizer to ensure uniform input lengths by truncation and padding. The dataset was then divided into validation and training sets to maintain an even distribution. A custom dataset class was created to handle the tokenized data and then processed using batch-based loading techniques.

A pre-trained transformer model was fine-tuned for binary classification, leveraging an optimized training strategy that included adaptive learning rate scheduling, gradient accumulation and mixed precision training to enhance computational efficiency. The model was then trained for multiple epochs using a batch-based approach which had regular checkpoints to monitor progress and prevent overfitting.

"Linear SVC is a supervised machine learning algorithm derived from Support Vector Machine (SVM). It uses a vector method to classify tweets into various classes. A decision boundary also known as the hyperplane is constructed between two classes and a datapoint is classified between these two classes".

Linear SVC differs from SVM mainly in the loss function used by default, unlike kernelized SVMs, Linear SVC uses a linear kernel making it computationally more efficient for text-based tasks and dealing with sparse data.

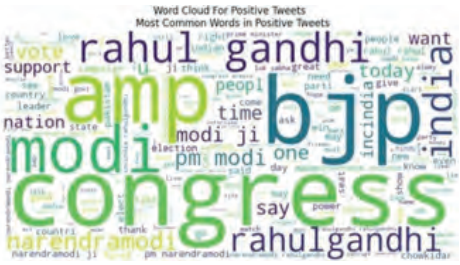

Fig. 6 Word Cloud of Positive Tweets on BJP and Congress in the 2019 Lok Sabha Elections, Highlighting the Most Frequently Used Words.

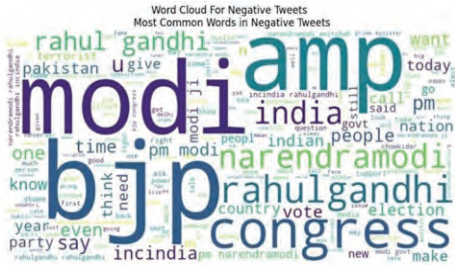

Fig. 7 Word Cloud of Negative Tweets on BJP and Congress in the 2019 Lok Sabha Elections, Highlighting the Most Frequently Used Words

RESULTS AND DISCUSSIONS

The sentiment analysis and prediction for the election of Lok Sabha 2019 has been tested on Juptyer Notebook (JN) with a 64-bit processor. The models were evaluated using multiple evaluation metrics like Precision, Recall, Accuracy and F1-score.

Precision measures how many of the predicted positive instances are actually correct. It would be useful in scenarios where false positives would prove to be costly.

$$Precision(A) = \frac{True\ Positives}{False\ Positives + True\ Positives} \quad (1)$$

Recall measures how many actual positive instances were correctly identified. It would be useful in scenarios where a false negative would prove to be costly.

$$Recall(B) = \frac{True\ Positives}{False\ Negatives + True\ Positives} \quad (2)$$

The F1-score is the harmonic mean of precision (A) and recall (B), providing a balanced and appropriate measure when both metrics are important. This is mainly used during an unequal class distribution.

$$F1\ Score = 2 \times \frac{A \times B}{A + B} \quad (3)$$

Based on the above metrices Table 1 gives the comparative analysis of the various models used in this research.

Table 1 :Comparison of various models

S. N.	Model	Accuracy	Precision	Recall	F1 Score
1.	CNN	94.5	94	95	95
2.	BERT	92.99	92.74	96.24	94.46
3.	Linear SVC	81.43	81.01	80.2	81

CONCLUSION

This research involves analysis of deep learning and conventional machine learning models for text classification, focusing on metrics based on accuracy, recall, precision and F1-score. Amongst all tested models CNN with 20% of the data for testing and 10% for validation attained the highest accuracy at 94.50%. This underscores the potential of deep learning. BERT had very good recall (96.24%) and precision (92.74%) scores, thus performing outstandingly in capturing complex patterns; however, traditional model such as Linear SVC was much faster but less accurate with an accuracy of 81.43%. The future scope of this study can include tweets of different dialects of Indian origin.

REFERENCES

1. Payal Khurana Batra, Aditi Saxena, Shruti and Chaitanya Goel, “Election Result Prediction Using Twitter Sentiments Analysis” in Sixth International Conference on Parallel, Distributed and Grid Computing (PDGC)
2. Sharma P, Moh T-S (2016) “Prediction of Indian election using sentiment analysis on Hindi Twitter”. 2016 IEEE International Conference on Big Data (Big Data) 1966–1971.
3. Vyas R Indian Election Tweets (2019) [Kaggle]
4. Lydia A, Kumar MN, Nagendra PRS, Dilliraj S, Sumathi S (2024b) “Election result prediction using Twitter Sentiments analysis”. IJIRCCE 12–12
5. Lan Z, Chen M, Goodman S, Gimpel K, Sharma P, Soricut R (2019b) ALBERT: “A lite BERT for self-supervised learning of language representations”. arXiv (Cornell University).
6. https://doi.org/10.48550/arxiv.1909.11942.

Neural Network Model for Pneumonia detection: An Empirical Analyses of Chest X-ray Classification

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ABSTRACT

Pneumonia is a serious lung infection that mainly affects children, the elderly and individuals with weak immune systems. Early detection is crucial for effective treatment, but traditional chest X-ray interpretation is time-consuming and relies on expert radiologists, which can lead to delays. Deep learning and Machine learning algorithms, especially Convolution Neural Networks have proven to be effective in the detection of pneumonia. This research focuses on evaluating six popular deep learning models namely VGG-16, VGG-19, Inception V3, EfficientNet, ResNet50, and MobileNetV2 towards pneumonia image classification. Empirical analysis suggests that VGG-19 is the most efficient model with high precision value of 99.67, recall of 99.67 and AUC value 0.9708. VGG-16 also performed well with an accuracy of 96.76%, it also exhibited the highest precision and recall values of 99.67. The EfficientNet model performed well in AUC (0.9753) but had low accuracy value. MobileNetV2 with an accuracy of 38.31% and ResNet50 with a classification accuracy of 63.57% struggled, while Inception V3 has shown a high loss value if 11.7858, making these methods a less suitable choice for Pneumonia classification. Results suggest that VGG-16 and VGG-19 are the two most appropriate convolution networks for the classification of Pneumonia images.

KEYWORDS *: Pneumonia, Image classification, Convolution neural network.*

INTRODUCTION

Pneumonia is one of the important diseases to be discussed as it is far more dangerous than any other disease. Pneumonia is such a disease where the lungs of the patient get affected and the whole respiratory system gets weakened also it is far more serious when it comes to children and people with weak immunity. United Nations Children Funds (UNICEF) had a major role in helping the children and providing help for their development of children, according to UNICEF there were around 8 lakh children who were under the age of five died due to pneumonia, therefore it is necessary to look forward to such disease and treat them as early as possible. For doctors to treat pneumonia patient needs to detect the pneumonia first so that early detection of pneumonia will help the patient recover quickly and save many lives. Scientists have been looking forward to technologies such as artificial intelligence to detect pneumonia. Due to advancements in technology, there is a special type of AI used by scientists called a convolution neural model which is a core concept of deep learning and machine learning. This CNN will go through many X-ray images and analyze all the lungs through the X-ray images and give the result as to whether the lungs are healthy or need to be treated due to pneumonia.

There was a study made by Mabrouk et al in 2023 which gave a pre-trained CNN model such as denseNet169, Mobilenetv2, and vision transformer. When such a model was used to detect pneumonia, it gave an accuracy of 93.88% [1]. There was one more scientist named Tripathi et al who studied one of the most important sections for pneumonia detection which is CNN architecture in 2021 which was highly useful for increasing the efficiency and accuracy in the detection of pneumonia [3]. Similarly, one more study based on

the CNN model was made by Pal and Das in 2022 they worked on the capabilities of the model to give higher accuracy for the detection of pneumonia [2]. After that Gupta worked on these CNN models and showed us the use of effectively diagnosing pneumonia.

This research made us understand the evaluation of CNN models and their real powers to be used for the detection of pneumonia from X-ray images.

LITERATURE ANALYSIS

Pneumonia is a harmful and serious lung disease among children, senior citizens, and all the people who have weak immunity.

To treat pneumonia patient's chest X-rays are used by doctors but it is a very difficult and time-consuming process to detect the symptoms of pneumonia through chest X-ray images as there are many variations (lobar, bronchopneumonia). Also, in some regions, there is an absence of radiologists which is a huge obstruction in pneumonia detection. This study works more on modern technology and computational methods to gain maximum accuracy and efficiency for detecting pneumonia [11]. This study works purely on AI models and it also involves some techniques on which AI models work like radionics, fractal dimension, and super pixel which increases the accuracy of AI models for pneumonia detection by up to 99% [5]. Dropout a concept of deep learning and machine learning is used as building blocks in our AI models for detecting pneumonia. Szepesi et al came up with a model that was tested on X-ray images for normal healthy lungs and even tested on pneumonia patients [8]. The convolution neural networks are used to scan the whole X-ray images and analyze the pattern and feature which in turn improves the efficiency of diagnosis and treatment of pneumonia. The recent case study represents an immense usefulness of AI models for pneumonia detection which involves machine learning as a major part of it. One more research came up with the idea of a special computer that consists of more than one CNN model that detected pneumonia with 98.81% accuracy [13]. One of the most refined works is an automated system leveraging a convolution neural network for the detection of pneumonia [8].

Utilizing pre-trained CNN models to detect pneumonia through chest X-ray and determine whether the lungs are in normal condition or in abnormal condition is one of the most reliable and efficient learning approaches toward pneumonia diagnosis and treatment [14]. Pneumonia is one of the most serious problems among people and it is necessary to improve treatment and diagnosis. The use of AI especially CNN has enhanced the accuracy and efficiency of pneumonia detection. Studies leveraging CNN-based architectures such as VGG-16 and ensemble models, have demonstrated exceptional performance achieving accuracies exceeding 96% in pneumonia classification.

METHODOLOGY

In this particular section, we are going through a step-by-step procedure and basic view of our structure and its strategies to work on it, here this includes collection of information, datasets, preprocessing, and preparation of our model.

Dataset

The dataset this used consists of 5800 chest X-ray images obtained from Kaggle (2016) [1]. It is divided into two types: Pneumonia and normal. Each type is further divided into training and testing which helps us in developing a model and evaluation in medical imaging tasks.

Data Pre-Processing

To enhance model performance and ensure consistency, several preprocessing steps were applied to the dataset: Image Loading & Resizing: All images are there using OpenCV which is resized to 150x150 pixels to standardized input dimensions. This resizing is done so that this can reduce the complexity while keeping the essential image features. Data Augmentation: To improve our model and prevent overfitting and also for standard augmentation techniques including Rotation and Flipping: Random rotations to simulate real-world variations and horizontal flipping to introduce viewpoint variations. Brightness Adjustment: The pixel intensity of images is Normalized to support brightness adjustment thus facilitating better images for classification. Data Shuffling: The dataset was shuffled using the Scikit-learns shuffle function to prevent learning bias. Train-Test Split: The dataset is divided into 80% training and 20% testing subsets using the train-test-split function (random state=42) to ensure reproducibility. Label

Encoding: The categorical labels were converted into numerical values for binary classification, Pneumonia affect ted X-ray images are labeled as 1 while normal X-ray images are labeled as 0.

CNN Models

This section of the paper discusses the Six Neural Network models selected for this study.

VGG-16: This is a special model which is used to analyze images. It consists of 16 layers which helps us to learn and identify the patterns in images like identifying the disease. It was trained by understanding a huge number of pictures. Due to this VGG16 is used in healthcare to detect diseases like pneumonia. It helps us to detect the disease faster and with more accuracy.

VGG-19: This is a model that has 19 layers and becomes even more efficient and accurate for recognizing and identifying the patterns in an image. It is very good at understanding new images. When the experts are limited, it helps the doctor to make faster, more accurate diagnoses.

EfficientNet: EfficientNet is a computer program designed to analyze images efficiently. It uses a method which necessary for the model because it balances the size, depth, and detail, making it both powerful and fast. Trained on a huge number of pictures its great understanding helps us to detect the diseases in medical sector.

Inception V3: Its smart design makes it very efficient and powerful even for a complex task like detecting diseases in medical images. Trained on a huge collection of pictures, its great understanding such as chest x-rays and can also help in identifying pneumonia. Its ability to pick up details at different scales makes it a reliable tool for healthcare, especially in places where expert help is limited.

Resnet50: Residual Network, solves the problem of vanishing gradients usually encountered by very deep neural networks. It does so by using residual learning, where shortcut connections (or skip connections) allow the Network to skip over layers, thus making it easier and more efficient to train deeper models, while also mitigating degradation. The identity mappings used in Resnet enable important features to be preserved as well as allow improved gradient flow, making it possible for models to train deeper networks without performance loss.

Mobile Net V2: MobileNetV2 is a Convolution neural network architecture which is a lightweight model used popularly for effective image classification designed for handy devices like mobiles. It is an advancement to the MobileNetV1 model with inverted residual blocks and linear bottlenecks for higher computational efficiency while maintaining accuracy. These 5 models use depth-wise separable convolutions, drastically reducing the number of parameters and operations compared to traditional CNNs, making them suitable for real-time applications. All selected models are implemented using TensorFlow. The models were trained using the Adam optimizer for adaptive learning rate adjustments, and the Softmax activation function was applied in the final classification layer to output probability scores for the two classes.

Model Training

The model that was trained was on the processed dataset which was done using TensorFlow's high-level framework. The optimizer which was chosen to improve learning was the Adam optimizer and the Softmax activation function was used for making predictions. The dataset which was used was divided into 80% for training and 20% for testing to ensure proper evaluation. To make the computation more efficient batch processing was applied and cross-entropy was used as the loss function, to improve classification accuracy. Cross-entropy as expressed in equation (1), C is the total number of classes, y_i is 1 if the sample belongs to class i (otherwise 0), $\hat{y}_i$ is the predicted probability, and a log is a natural logarithm.

$$L = -\sum_{i=0}^{n} \hat{y}_i \log \hat{y}_i$$

RESULTS AND DISCUSSION

This section presents the performance evaluation of the models used, i.e., VGG-16, VGG-19, EfficientNet, Inception V3, and DenseNet on the Pneumonia X-ray images. The trained models were accessed based on accuracy, precision, recall, cross-entropy loss, and AUC. Accuracy is the percentage of correct predictions made

showing the overall correctness of the overall model. Precision checks the number of correct predictions thus helping in reducing false alarms. Cross entropy Loss measures how well the model generalizes to unseen data. The lower the value the better the performance is. AUC (Area Under the Curve) evaluates the model's ability to differentiate between pneumonia and normal cases.

The comparative analysis of deep learning models for pneumonia classification using chest X-rays reveals significant variations in performance across different architectures as shown in Table 1. Among the tested models, VGG-16 demonstrated the highest accuracy (96.76%), suggesting its strong capability in identifying pneumonia cases correctly among all the chest X-rays given. However, its relatively lower AUC (0.8404) indicates potential difficulties in distinguishing borderline cases. VGG-19, on the other hand, proved to be the most balanced model, achieving a high AUC (0.9708), calculated using Equation 2, precision (99.67%), and recall (99.67%) as shown in Fig. 1, making it highly reliable for pneumonia detection with minimal false positives and false negatives.

EfficientNet, despite achieving the highest AUC (0.9753) and the lowest loss (0.5165), exhibited a significantly lower accuracy (52.79%), indicating challenges in generalizing to unseen data. Inception V3 performed well in terms of AUC (0.935), precision (93.43%), and recall (93.43%), but its extremely high loss (11.7858) raises concerns about model stability and convergence issues. Furthermore, ResNet50 and MobileNetV2, despite showing high precision and recall, failed to achieve strong classification accuracy (63.57% and 38.31%, respectively), suggesting that these architectures may not be well-suited for the classification of the chest x-rays without further optimization. ResNet50 achieved a competitive AUC of 0.962 but still underperformed in overall accuracy, while MobileNetV2, designed for efficiency in low-resource environments, struggled with a relatively lower AUC (0.9584) as shown in Figure 1. The high recall values across most models indicate a general tendency to correctly identify pneumonia cases, yet the variations in AUC and accuracy highlight the challenge of ensuring both sensitivity and specificity in real-world clinical applications.

Overall, VGG-19 stands out as the most robust model for pneumonia classification, balancing accuracy, precision, recall, and AUC, making it a suitable choice for medical diagnostic purposes. Further improvements through hyperparameter tuning and dataset augmentation may enhance the performance of other models, particularly EfficientNet and ResNet50, to optimize their clinical applicability.

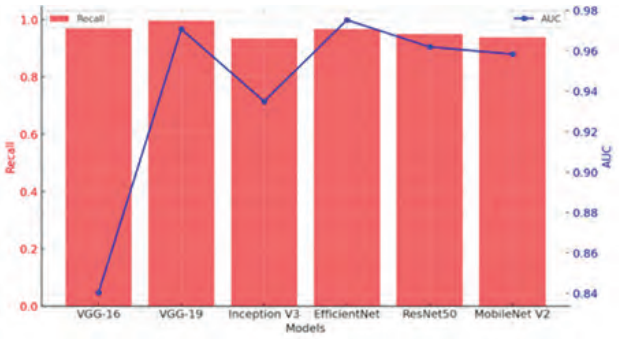

Fig. 1: Experimental results of selected models in terms of Recall and AUC

Table 1: Performance scores of all the selected Neural networks

Classifier Model	Loss	AUC	Accuracy	Precision	Recall
1. VGG-16	1.1309	0.8404	0.9676	0.9679	0.9699
2. VGG-19	1.6525	0.9708	0.9108	0.9967	0.9967
3. Inception V3	11.7858	0.935	0.9121	0.9343	0.9343
4. EfficientNet	0.5165	0.9753	0.5279	0.9676	0.9676
5. Resnet50	1.0357	0.962	0.6357	0.9505	0.9505
6. Mobile Net V2	0.6176	0.9584	0.3831	0.9377	0.9377

CONCLUSION

Pneumonia is a serious problem that affects the lives of multiple people worldwide. Chest X-rays when analyzed using Convolution neural network models can make the disease identification task easier and accurate. This study aims to test a set of six deep learning models to improve pneumonia detection using X-ray images. Extensive experiments are conducted to evaluate the performance of each of the selected models. Evaluation

methods used for the study are Prediction accuracy, Precision, Recall, AUC and Loss value. Each of the six models is evaluated by overall balance, efficacy, and metric outcomes. Among the selected methods, VGG-19 demonstrated the most balanced performance, with a high AUC of 0.9708, precision value of 99.67%, and a high recall value of 99.67, showing it be a reliable choice for medical image classification. VGG 16 model achieved the highest classification accuracy i.e., 96.76%, but it has a comparatively lower AUC value of 0.8404. EfficientNet had the highest AUC of 0.9753 but a very low accuracy of 52.79, which shows the issue of generalization. Inception V3 per formed fairly with an AUC of 0.935 but experienced an excessively high loss of 11.7858. The performance of ResNet50 and MobileNetV2 is found to be fairly poor. This study concludes that VGG-19 is the most fitted Convolution Neural Network for Pneumonia X-ray image classification

REFERENCES

1. Mabrouk, A., Díaz Redondo, R. P., Dahou, A., Abd Elaziz, M., & Kayed, M. (2023). Pneumonia Detection on Chest X-ray Images Using Ensemble of Deep Convolutional Neural Networks
2. Pal, J., & Das, S. (2022). A Convolutional Neural Network (CNN)-Based Pneumonia Detection Using Chest X-Ray Images. In Using Multimedia Systems, Tools, and Technologies for Smart Healthcare Services (pp. 63–82). IGI Global.
3. Tripathi, S., Jalal, A. S., & Agrawal, S. C. (2021). Optimal Pneumonia Detection Using Convolutional Neural Networks from X-ray Images.
4. Gupta, S., Panwar, A., Kapruwan, A., & Kumar, A. (2021). A Comparative Analysis of Deep Convolution Layered Machine Learning Approaches for Detection of Pneumonia from Chest Radiographs.
5. Ortiz-Toro, C., García-Pedrero, A., Lillo-Saavedra, M., & Gonzalo-Martin, C. (2022).Automatic detection of pneumonia in chest X-ray images using textural features. Computers in biology and medicine, 145, 105466.
6. Szepesi, P., & Szilágyi, L. (2022). Detection of pneumonia using convolutional neural networks and CNN. Biocybernetics and biomedical engineering, 42(3), 1012-1022.
7. GM, H., Gourisaria, M. K., Rautaray, S. S., & Pandey, M. A. N. J. U. S. H. A. (2021). Pneumonia detection using CNN through chest X-ray. Journal of Engineering Science and Technology (JESTEC), 16(1), 861-876 .
8. Cillóniz, C., Torres, A., & Niederman, M. S. (2021). Management of pneumonia in critically iAliberti, S., Cruz, C. S. D., Amati, F., Sotgiu,
9. Gupte, T., Knack, A., & Cramer, J. D. (2022). Mortality from aspiration pneumonia: incidence, trends, and risk factors. Dysphagia, 37(6), 1493-1500.
10. Kundu, R., Das, R., Geem, Z. W., Han, G. T., & Sarkar, R. (2021). Pneumonia detection in chest X-ray images using an ensemble of deep learning models. PloS one, 16(9), e0256630.
11. Alapat, D. J., Menon, M. V., & Ashok, S. (2022). A review on detection of pneumonia in chest X-ray images using neural networks. Journal of biomedical physics & engineering, 12(6), 551.
12. Sharma, S., & Guleria, K. (2023). A CNN model for the detection of pneumonia from chest X-ray images using VGG-16 and neural networks. Procedia Computer Science, 218,357-366.
13. Li, S., Mo, Y., & Li, Z. (2022). Automated pneumonia detection in chest x-ray images using deep learning model. Innovations in Applied Engineering and Technology, 1-6.
14. Gupta, P. (2021). Pneumonia detection using convolutional neural networks. Science and Technology, 7(01), 77-80.

Leveraging Smart Contracts for Secure and Automated Examination System

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ABSTRACT

In this paper, a scheme for smart online exams based on the application of blockchain for improving the security and integrity in question sharing, scoring and result distribution has been suggested. The question papers are a mixed difficulty level of questions prepared by various experts and organizations. Once the questions are prepared, they are placed on the blockchain, and the access key to them is encrypted using Lock Puzzle mechanism, so that no central body has access to it, hence paper leak is avoided. At the time of examination, the questions are decrypted and made available to the students taking the exam, their answers are also placed on the blockchain using smart contracts. The system matches the students' answers with the pre-decided solutions thus calculating and displaying the scores in real time. Briefly, this paper puts forward a secure interface for conducting and assessing online examinations, with blockchain and smart contracts being utilized for storage, scoring and result distribution to provide uniformity among students and exam conducting agencies.

INTRODUCTION

With more and more exams being conducted in an online mode, several challenges have been encountered. It includes security issues, paper leaks, and unfairness in grace marks distribution. This can severely dent the trust in the examination process, and over time, impact how fair the students feel the exam conducting authorities are. A recent example of such vulnerabilities is the NEET paper leak scam. It is a series of issues that have led to the dilution of the examination's integrity. They include question paper mistakes, arbitrary grace marks and paper leaks. This raised several questions regarding the capability of the management systems to provide transparency.

Blockchain has brought a revolution in the realm of technology. In blockchain when a transaction occurs it has to experience validation, a process where the involved parties must reach a mutual agreement to allow that transaction. In this way blockchain removes the need for a centralized authority to control all data, ensures transparency, security and immutability of data.

This research aims to integrate blockchain technologies with online examinations to maintain integrity and transparency of the exam process. It presents a unique approach where the questions for the exam are created by different experts and bodies. These questions include a mix of difficulties and are distributed equally while creating the papers. All the created papers are stored in the blockchain in an encrypted format, the key that is used for this process is not just accessible to the central exam authority, it is encrypted using the time lock puzzle on the blockchain. The time lock puzzle requires the time of the exam to be achieved before the puzzle is unlocked. The answers submitted by the student are similarly stored in the blockchain and are autonomously compared with predefined answers for the questions. This allows instantly available scores for the student to check upon logging in with appropriate credentials.

LITERATURE REVIEW

In already existing online examination systems, there exist vulnerabilities such as paper leaks, unfair grading, manipulation of results and lack of transparency. A

recent example of such vulnerabilities is the NEET[1] paper leak scam. It includes a series of issues that have compromised the integrity of the examination. These include errors in questions papers, arbitrary grace marks, paper leaks.

This post highlights the recent NEET scam that has affected the system and reveals deep flaws in the education system. The major flaws highlighted in the scam were -

1. Errors in question papers
2. Arbitrary grace marks
3. Allegations of fraud and manipulation
4. Middlemen facilitating cheating

Some systems are attempting to address these issues by utilizing blockchain technology and secure formats. Some researchers tried to examine the possibilities for conducting online exams in the absence of proctor [2]. They have provided extensive information about the common characteristics of students indulging in malpractices based on which they have provided some strategies for developing a framework for online testing, along with additional information. Techniques like using respondus lockdown browser (rdl) in online exams are implemented to ensure the integrity of the exam process. Mukta et.al. have played a role in the development of the fuzzy logic where a robust approach that prioritized student assessments has been created[3]. Teja et.al. have suggested employing Convolutional Neural Networks (CNN) that are used to accurately identify a student during an online exam. However, CNN does not possess the capability to analyze a student's position.

Many schools are now using online platforms for exams, especially for middle and high school students. The most popular online tests require candidates to provide a username and password, then access a selection sheet to answer the questions. Though, there exists many shortcomings in the system, and unfair tests can be made by using incorrect passwords. It has been observed that it is important to use secure methods to protect against this kind of problem. This research introduces the blockchain principle for online exam security.

Institutions can easily gather their own data from trustable sources like books, internet, articles, etc without relying on central services to provide them the necessary data. It enhances data security and non-reliance on a certain central authority. A blockchain model was proposed which would eliminate the need for institutions to access applications and services. To ensure consistency of data between students and the platform and protect the integrity of the questionnaire, blockchain was used [4].

Soo Young Shin and Anik Aslam proposed a new intelligent learning method using the blockchain concept for sharing problems [5]. A two-stage encryption process is planned for encrypted question papers (QP). In the first stage, the QP is protected using the timestamp. In the second stage, the previously encrypted QP is re-encrypted using the timestamp, salt hash and the hash of the previous QP. These encrypted QPs are stored in the blockchain along with smart contracts that help users unlock the selected QPs.

A QP selection algorithm is also proposed that randomly selects QPs. Security assessments are done to illustrate the feasibility of different attack schemes. Finally, the effectiveness of the implementation is verified through actual implementation and its superiority over existing implementations is demonstrated through comparative studies based on different features. The conclusions drawn include that the increase in QPs also increases the size. Each block contains the QP, time and hash of the previous block. As the number of QPs increases, the encryption time also increases. Overall, this is a promising approach to provide sufficient security to reduce data leaks.

Another solution for online examinations using blockchain for question storage, answer storage and ethereum wallet for payment of exam fees has been provided in the study [6]. The structure that the proposed solution follows includes Student Registration, Login, Online exam, and finally Evaluation &

Results. Once the registration is complete a unique blockchain address is created. Next phase is the instructions, in this phase student logins using registered email and reads the instructions on the screen carefully. In the examination phase the questions are decrypted and delivered to the student, student answers are sent to blockchain via smart contracts, which contain the student answers, transaction hash for that user and

timestamp. Finally, in the evaluation phase the answers are compared manually or in an automated manner using smart contracts. The final results are stored in the blockchain and students can login to view the results, thus ensuring transparency and immutability.

A model which is autonomous and decentralized is used to administer University Exams for security and safety [7]. Many universities face challenges such as maintaining integrity, preventing malpractices, confidentiality of examination of records and creating an efficient management for smooth conduction of the exam process. It describes an efficient decentralized model and autonomous system for exam management. This model is based on Blockchain Technology and Internet of Things (IoT). It basically maps the common use-cases in standard examinations to major elements of blockchain i.e. is Smart Contracts, Cryptography, IOT etc.

The education system and the central monitoring system were significantly impacted in several ways. First, a widespread erosion of trust was observed, as confidence in the fairness and integrity of the system was severely undermined. As a result, many deserving candidates were unfairly side-lined or overlooked, leading to a sense of injustice and disillusionment. Moreover, the overall quality of education was affected, as standards were compromised and the focus shifted away from genuine merit and learning.

The solutions that the government should be able to implement to curb such kind of scams are -

1. Strengthen exam security
2. Transparent admission process
3. Severe penalties

Yusuke Kaneko et.al[8] proposes a model without a centralized authority which has a sustainable exam administration with enhanced reliability while using a public blockchain and enhanced transparency. Results which cannot be tampered are recorded in the blockchain with the hash values of correct answers, decision condition, and decision result. The proposed method used Bitcoin Core which had over 100 participants to conduct a Capture The Flag(CTF). The results obtained were flawless confirming the viability of a blockchain based decentralized solution.

BLOCKCHAIN SOLUTION

Blockchain technology can be thought of as a special kind of digital notebook. Instead of being kept in one place, that notebook is shared across many computers at the same time. Each time a new note is added, it is checked by many participants before it is safely recorded. This process is managed by complex math rules, yet it can be explained in simple terms as a way to make sure that no one can quietly erase or change what has been written before.

Because the notebook is copied everywhere, it becomes almost impossible for mistakes or bad actors to sneak in unnoticed. If someone tries to alter a past entry, the other copies will not match, and so the change will be rejected. In this way, trust is built without needing any single person or group to be in charge. Instead, the system as a whole is trusted because of the checks and balances that are always at work behind the scenes.

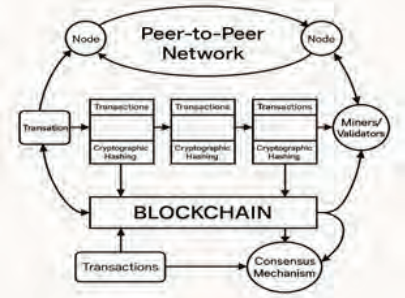

Fig. 1. A decentralized network–wide ledger is shown, where transactions are grouped into cryptographically linked blocks and added by consensus

Blockchain is useful for more than just money or digital coins. Any kind of agreement, like a contract or proof of ownership, can be stored in the same kind of shared notebook. Once stored, it can be relied upon by everyone involved, since it cannot be secretly changed later. This is considered helpful for many areas, such as supply chains, voting systems, and digital art, where confidence in records is very important.

The security and openness of blockchain brings new chances for people to work together. When systems are transparent yet protected by strong rules, new ideas and services are encouraged to grow. In the future, more everyday activities could be managed through blockchain so that fewer middlemen are needed. In this way, more direct connections might be created among

people and businesses, with less worry about mistakes or fraud.

All records are kept more safely when they are spread out instead of keeping them in one single place. When blockchain is used, data is locked away by complex math puzzles so that no one can quietly change what has already been stored. This method is considered helpful because a clear history is always kept, and every change is watched by many helpers at the same time. In this way, mistakes or sneaky edits are stopped before they can happen.

Similarly exam questions and answers are treated in the guarded way. Each question could be placed into a block and given a special code before being shared. When an answer is handed back, it would also be put into a new block and given its own code. Because everything is locked together in order, it would be very hard for anyone to swap out a question or sneak in a wrong answer. This would make sure that the papers seen by students and the scores given by teachers are both true and fair.

In the future, more trust is likely to grow between students, teachers, and schools if exams are managed using blockchain. It could be assured that once an exam is closed, it cannot be reopened or altered. Also, it would be possible for schools to check quickly that the work they see really came from the moment it was taken, since each entry is stamped by time and by the network of helpers. All of this could lead to a world where cheating is made much more difficult, and confidence in the exam process is quietly strengthened

PROPOSED SYSTEM

The proposed system will provide a reliable and transparent Online Examination System via blockchain technology and Lock Puzzle to address issues such as paper leaks, rank manipulation, and lack of transparency. The system safeguards question papers and saves them securely on the blockchain. In a way the key to decrypt the questions doesn't exist without actually waiting for the time of auto decryption. Decentralization ensures that no one has custody of the keys in total, reducing the likelihood of leaks or misuse.

During the examination, the questions are auto decrypted where the time lock puzzle makes the questions open. This allows questions to be decrypted and delivered securely to the students through a secured interface. Student responses are submitted and saved on the blockchain through smart contracts, which utilize public key cryptography to verify each submission is directly sent by the student. This prevents middleman tampering and ensures submission integrity.

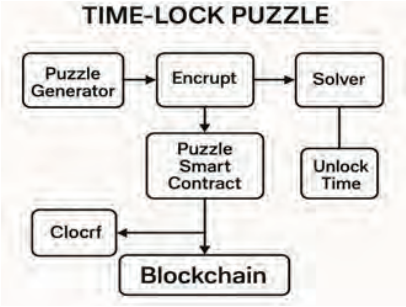

Fig. 2. The smart contract checks the on-chain timestamp against the predefined unlock time and only allows puzzle decryption once the required time has passed.

After the successful completion of the examinations, the answers are posted by the student and automatically stored on the blockchain system using smart contracts. Once submitted, the answers are matched against the pre-agreed solutions through the same smart contracts. This automated verification ensures that marks are calculated instantly and securely, after which they are stored on the blockchain ledger. Students are then able to log in, view their marks, and verify their ranks. This enhances the transparency and trust in the evaluation process.

However, it is important to note that the results released immediately after the exam are considered provisional. These initial scores are generated based on a published answer key stored within the blockchain system. Students are given the opportunity to review their results and challenge any answer they believe has been incorrectly evaluated. The challenges are submitted within a defined window, during which they are reviewed by authorized evaluators, depending on the system's implementation. Once the review process concludes, the final scores are updated and locked into the blockchain, ensuring that they cannot be tampered with thereafter. This feature ensures fairness and provides recourse for correction, thus enhancing the credibility of the system.

This method introduces several notable benefits. It is tamper- proof, as blockchain technology prevents any modification to the stored questions or answers once

they have been committed. By utilizing decentralized key management through Lock Puzzle technique, the problem of questions leaking before the exams is eradicated, which not only enhances security but also significantly reduces the risk of question paper leaks. Furthermore, the use of smart contracts allows for instant generation of provisional results, which increases the transparency of the examination process while allowing flexibility for appeals and corrections before finalization of student ranks.

Despite all the benefits, there are some issues with the system. Scaling the system to millions of participants is an optimization problem, and accessing the questions before the exams is not possible in any case of system discrepancy. Future enhancements could include adding AI for plagiarism checking and fingerprint authentication to enhance the reliability and functionality of the system.

CONCLUSION

It has been observed that several problems faced by online exams like paper leaks, result manipulation and lack of transparency are key issues with the exams. However, it can be seen how growing technologies like blockchain, encryption algorithms and techniques, and smart contracts can be applied and used to overcome these challenges. Currently existing systems like multiphase encryption, timestamp locks, and automated scoring mechanisms, portray that decentralized approach can enhance and improve security, transparency and overall confidence in the exam process. Though many of these systems still lack the idea of an almost perfect solution, specifically when it comes to eliminating centralized control over significant and necessary components like encryption keys and a centralized server.

A brief overview of a proposed system that builds over these past solutions and makes significant effort to combine them has been provided. Lock Puzzle and blockchain, being the bottleneck of this solution, addresses the major weaknesses found in the current system. Although the idea itself is promising, there is a lot to explore particularly in terms of scalability and implementation of this at a larger scale.

To summarize, though there has been significant progress in addressing the vulnerabilities of the online exams, this research highlights that some gaps still exist. The literature provides a foothold for future studies particularly in designing systems that are tamper proof as well as scalable while being user friendly. Using upcoming technologies and integrating them into the traditional examination systems could transform the way exams are conducted, ensuring fairness, trust and transparency for all the parties involved in the process.

REFERENCES

1. The NEET Scam: A Call to Protect Our Students and Education System[Last Accessed: 15/09/2024].
2. G.R. Cluskey Jr, C.R. Ehlen and M.H. Raiborn, Thwarting online exam cheating without proctor supervision," Journal of Academic and Business Ethics, vol. 4, no. 1, pp.1–7, 2011.
3. M. Goyal, D. Yadav, and A. Choubey, "Fuzzy logic approach for adaptive test sheet generation in e-learning," in 2012 IEEE International Conference on Technology Enhanced Education (ICTEE), 2012, pp. 1–4.
4. Manawar, Albert. (2023). An Innovative and Secure Platform for Leveraging the Blockchain Approach for Online Exams. Aptisi Transactions on Technopreneurship (ATT). 5. 99-108. 10.34306/att.v5i1.314.
5. Islam Abhi, Anik & Kader, Md Fazlul & Shin, Soo. (2019). BSSSQS: A Blockchain-Based Smart and Secured Scheme for Question Sharing in the Smart Education System. 17. 174-184. 10.6109/jicce.2019.17.3.174.
6. Vaidya, Bhaskar. (2024). Revolutionizing Online Assessment Security with Secure ExamChain: A Decentralized Approach. International Journal for Research in Applied Science and EngineeringTechnology. 12. 5127-5132. 10.22214/ijraset.2024.62803.

[7] Patil, Y.N., Kiwelekar, A.W., Netak, L.D., Deosarkar, S.B. (2021). A Decentralized and Autonomous Model to Administer University Examinations. In: Lee, SW., Singh, I., Mohammadian, M. (eds) Blockchain Technology for IoT Applications. Blockchain Technologies. Springer, Singapore. https://doi.org/10.1007/978-981-33-4122-7_6

[8] Yusuke Kaneko, Shuntaro Tanaka, Tomoyuki Kimura, Jun Okumura, Shigeyuki Azuchi, and Shigeyuki Osada. 2021. DeExam: A Decentralized Exam Administration Model using Public Blockchain. In Proceedings of the 2021 3rd Blockchain and Internet of Things Conference (BIOTC '21). Association for Computing Machinery, New York, NY, USA, 1–7. https://doi.org/10.1145/3475992.3475993

Lost in Translation: Implementation of AI in Indian Language Learning Apps

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ABSTRACT

This paper presents the development of an AI-powered Marathi language learning application designed to make regional language acquisition more interactive, accessible, and effective. The application integrates speech recognition using the wav2vec2 model for real-time pronunciation practice, and text-to-speech synthesis with VitsModel to help learners hear accurate pronunciation in Marathi. It also features a conversational AI chatbot, built with Langchain and integrated with ChatGroq (llama3-70b-8192), to provide 24/7 language support, doubt resolution, and casual conversation practice. Additionally, a community feature enables users to join or create chat rooms to engage with fellow learners and native speakers. This project demonstrates how open-source AI tools can be effectively combined to create a rich, Marathi-first learning experience. While still in early stages without formal user evaluation, internal testing confirms system stability and functional readiness, laying the groundwork for future user-centered refinement and scalability across other regional languages.

KEYWORDS *: Marathi language learning, Wav2vec2, VitsModel, Text-to-speech synthesis, Speech recognition, Conversational AI, Langchain, ChatGroq, LLaMA3, Language chatbot, Open-source AI tools, Low-resource language support, Real-time pronunciation feedback, Language learning app.*

INTRODUCTION

Tourism in Maharashtra is flourishing, drawing a diverse influx of visitors eager to experience its rich culture, history, and natural beauty. Yet, for many tourists, language remains a significant barrier—Marathi, the state's predominant language, is not widely supported by mainstream language learning platforms, and most resources available to travelers are limited to basic phrasebooks or generic translation tools. This gap not only restricts meaningful interactions with locals but also diminishes the depth of cultural immersion and independence that travelers seek. Traditional language learning methods, while valuable, often lack the immediacy, personalization, and contextual relevance required for effective on-the-go communication, especially in a tourism context [1].

The rapid evolution of artificial intelligence (AI) offers a transformative solution to these challenges. AI-powered language learning platforms can deliver highly personalized, adaptive, and interactive learning experiences, far surpassing the limitations of conventional approaches [2]. By leveraging advanced models in speech recognition, natural language processing, and conversational AI, these systems can provide real-time feedback, immersive practice environments, and dynamic conversational support [3]. For Marathi—a language underserved by global language apps—AI's potential is especially significant, enabling tailored instruction, instant pronunciation correction, and context-aware conversation practice that traditional resources simply cannot match [4].

Despite these technological advances, there remains a lack of comprehensive, AI-driven platforms focused specifically on Marathi for tourists. Existing solutions either do not support Marathi, offer only rudimentary features, or fail to address the unique needs of travelers, such as real-time conversation, authentic pronunciation feedback, and community-based practice [5]. As AI

continues to redefine language education by making learning more accessible, context-sensitive, and user-friendly, it also offers a platform for cultural exchange and community learning environments that enrich the travel experience [6].

This paper presents the design and implementation of an AI-powered application purpose-built to address these gaps. The objectives of this application are:

- To create an accessible, engaging, and tourist focused Marathi language learning platform.
- To harness AI models for real-time speech recognition, pronunciation feedback, and conversational practice tailored to travelers' needs.
- To provide a community-driven environment for peer interaction and cultural exchange.
- To demonstrate the effectiveness of AI-powered language learning in overcoming traditional barriers and enhancing the travel experience in Maharashtra.

By documenting the development, deployment, and unique features, this paper aims to contribute to the evolving discourse on AI in language education, particularly for low resource languages and tourism. It seeks to illustrate how AI can not only facilitate efficient language acquisition but also serve as a catalyst for deeper cultural engagement, ultimately redefining the paradigm of language learning for travelers.

BACKGROUND

The ongoing development of Artificial Intelligence has significantly influenced language learning methods by adding personalized, adaptive and interactive dimensions that cannot be achieved through traditional means. Various AI-based services such as speech recognition and natural language processing (NLP) serve to take the learner in the authentic moment and provide real-time feedback and conversational engagement in an immersive practice environment. It is critical in the case of underserved languages like Marathi, where such applications are often difficult to come by on current user-oriented language applications.

Many of the applications available to learners either do not support Marathi in a meaningful way or do not cater to their authentic needs, such as feedback on real-time conversation and authentic pronunciation of words. This indicates there is a need for tailored and dedicated applications for Marathi language learners, including tourists visiting Maharashtra.

There is no doubt that by developing an AI powered language learning application using advanced AI models for speech recognition, TTS synthesis and conversation engagement, the users can be provided a rich, Marathi-first learning experience.

LITERATURE REVIEW AND ANALYSIS

The Role of AI in Language Learning

Artificial Intelligence has emerged as a change agent in education, especially in language learning. According to research by Wei et al. (2023) assessing the impact of AImediated language instruction, significant improvements were found in the area of learning achievement in English, motivation to learn a second language, and self-regulated learning among students learning English as a Foreign Language (EFL). The findings promoted AI mediated strategies as a means to improve educational outcomes through real-time feedback, individualized pathways, adaptive delivery of content and the ability for learners to acquire a new language in a more efficient and inclusive manner [2].

Comparative Analysis of Existing Language Learning Applications

A thorough evaluation of popular language learning apps suggests that there are both strengths and limitations in current approaches. For instance, Duolingo uses Artificial Intelligence (AI) adaptive learning and includes speech recognition and feedback, which can target a wide range of learners through interactive learning. More specifically, on Duolingo, AI attempts to better understand and "think" about user responses, look for common grammar errors, and provide feedback to practice of language through pronunciation [7].

Busuu also uses a structured platform with feedback from native speakers so learners can have interactive vocabulary practice and grammar practice with audio, translation, and multiple activities to practice language. One study of the Busuu platform and members show 84% improvement in their knowledge of Spanish after using Busuu for 2 months, suggesting that they acquired knowledge [8].

Memrise is a great platform for vocabulary acquisition using spaced repetition learning and video immersion. Abarghoui and Taki (2018) examined the effectiveness of using Memrise (believing it or noting the perceptions of high school students using Memrise) on their perception of learning English as a Foreign Language (EFL). They found Memrise a useful, effective vocabulary learning tool with

a positive impact on their engagement and motivation[9]. While these strengths exist, these applications frequently do not provide advanced conversational practice and cultural context for languages that have a more regional component such as Marathi. The limitation here demonstrates a need for custom applications that are made to satisfy the specific needs for learning Indian languages.

The Importance of Regional Language Support

In the current state of the market, there is a noticeable absence of complete AI platform solutions for regional languages like Marathi. The existing ones do not have functionality for Marathi at all, and even those that do, have limited functionality and could hardly address the needs of learners who want real-time conversation, authentic pronunciation feedback, and community-based practice. This gap in knowledge is especially prominent for visitors or travelers in regions like Maharashtra, where Marathi is widely used. While traditional methods for language learning are valuable, they lack immediacy, personalization, or contextual relevance when it comes to real-time communication [4].

The Role of AI in Language Learning

Integrating AI into language learning software presents a solution to all these issues. AI models, for example the wav2vec 2.0 for speech recognition, allow for the possibility of immediate, individual feedback during immersive learning experiences. Researchers at Facebook state that this framework can enable automatic speech recognition models using as little as 10 minutes of transcribed speech data, showing its efficiency and adaptability [10].

Conversational AI chatbots based on model types such as LLaMA 3 improve language practice and uncertainty resolution and increase ease and access to learning. With the release of LLaMA 3, Meta opened up access to conversational artificial intelligence-based agents, which helps increase interactivity and responsiveness of language learning platforms [11].

Community and Cultural Engagement

Aside from technological innovations, incorporating community functions into language learning applications enhances belonging and cultural exchange. Apps that allow peer-to-peer interaction and collaborative learning provide a supportive environment that simulates real-life language immersion. This method not only improves language skills but also promotes cultural understanding and empathy. With its integration with community interaction, language learning applications can provide a complete experience that addresses linguistic and cultural aspects [12].

SYSTEM ARCHITECTURE AND METHODOLOGY

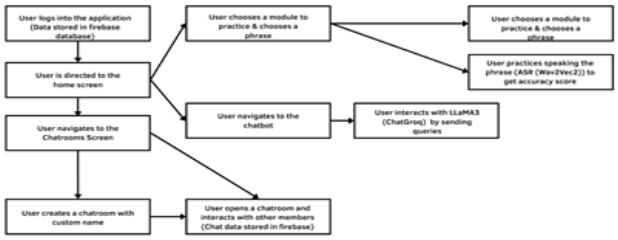

Fig. 1.User Process Interaction Flow Diagram

This Marathi language learning app gives users a fun, interactive experience using AI technology. It has an easy-touse design and uses smart tools for speech and language learning. Figure 1 shows the steps users go through in the app, including the different screens and what they can do on each one. When users open the app, they start by logging in. This login saves their profile, learning settings, and progress securely using Firebase Realtime Database. Because everything is stored in one place, users can keep learning on different devices and pick up where they left off.

After successfully logging in, users are taken to the home screen—the main screen of the app—where they see a number of learning modules grouped by topic, as well as some related vocabulary activities. These topics include greetings, travel, and health, among others. Users can navigate through the modules to find and pick certain Marathi phrases they want to learn. After picking a phrase, the app plays a native-like pronunciation using a Marathi TTS model first, so users can familiarize themselves with the proper phonetics. The user is then prompted to speak the phrase out loud. The ASR first processes the user's audio input in real time, which involves rendering the input into text and evaluating pronunciation accuracy against the native model output in seconds. As users repeat the phrase, they receive immediate feedback to improve their spoken pronunciation.

For users who want to be conversationally fluent in a language, the application includes an AI-powered chatbot that is always accessible from the home screen. This technology is powered by the LLaMA3-70B language model running on Groq's fast inference engine. Users can interact with the chatbot via text entry and receive intelligent, contextual responses in Marathi and English

that mimic real-world communication behaviour by allowing users to conduct multiturn, natural conversations.

Moreover, the app promotes community-based learning through chat rooms. Users have the option of sending messages to chat rooms in the home screen, and users can join a chat room or create a custom chat room name for group learning or themed discussions, all while exchanging messages and collaborating in real-time. All messages and data are managed and synchronized using Firebase. This peerto-peer experience increases user engagement and creates a socially enriching learning environment.

There are three main AI models that power the app's essential functionality. The app uses Wav2Vec2ForCTC to serve as the Speech Recognition (ASR) model, the fine-tuned version of Facebook's Wav2Vec 2.0 XLSR model, which was trained specifically for Marathi. Wav2Vec 2.0 uses a selfsupervised learning strategy and a Connectionist Temporal Classification (CTC) loss framework to transcribe the user's speech into text in real-time. It enables the app to deliver the user immediate, helpful pronunciation feedback.

For adding the Text-to-Speech (TTS) functionality, the app uses the VITS model from Meta's Massively Multilingual Speech (MMS) project, which is based on variational inference, normalizing flow, and GANs; VITS takes text inputs and produces natural and expressive Marathi speech. This feature significantly supports listening comprehension and makes content more accessible to all users, especially those with visual impairments. Finally, as for the Conversational AI, the chatbot is powered by ChatGroq, based on the llama3-70b-8192 model from Meta's LLaMA 3 series. As a multi-turn dialogue model with 8192-token long-context understanding, our chatbot provides intelligent and responsive conversational interactions. The chatbot acts as a virtual language tutor, and users can practice contextual dialogues with the chatbot while gaining confidence through real-time language use.

The application was developed with a structured methodology that involves modern development tools, cloud services that scale, and state-of-the-art AI models in order to support user needs. The frontend of the app was developed in JavaScript and TypeScript in the React Native Framework for cross-compatibility on Android and iOS mobile devices, with a database backend provided by Firebase. The development was done in Visual Studio Code using build/dependency tools such as Node.js and npm/yarn package managers. Git and GitHub were used for version control and collaboration within the development team. Development was structured to enable testing using the React Native Testing Library and obtaining a live preview of the several instances developed in Expo Go. The Firebase back-end was central to managing major user interactions in the application; Firebase was responsible for user authentication strategies, real-time synchronization of cloud data, and data storage. In this cloud service, learning history, preferences, and chat data are secured in the Firebase Realtime Database, allowing for a seamless and customized user-centric experience by eliminating lags and delays.

IMPLEMENTATION

Figure 2. represents the module selection and phrase learning view for the Marathi language-learning application. The module-selection view had a tidy and intuitive view with distinct modules consisting of clearly labeled icons and short titles to facilitate the flow of interactions. Once a module was selected, learners saw a list of the most useful English phrases contained in theme categories such as food and dining. Each phrase was accompanied by English text, Marathi translation, International Phonetic Alphabet (IPA) pronunciation, and English transliteration to assist in understanding. The module setup included interactive functions such as audio playback and student voice recording which provided learners with the opportunity to hear what correctly sounded, and a method to receive feedback after listening to their produced utterances. Learning a language through interactive authentically speaking words and phrases in TTS and STT was a dynamic, interactive, and effective way to acquire the target language.

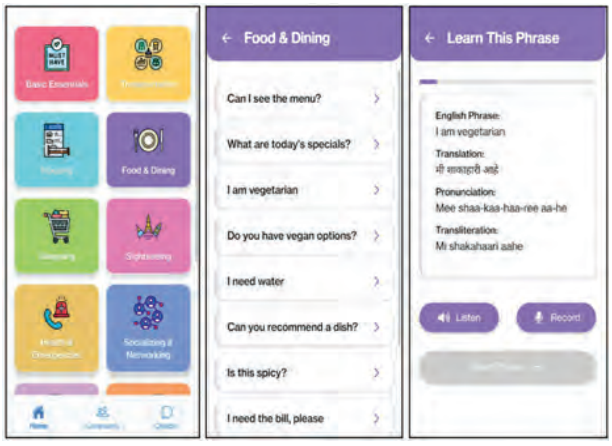

Fig. 2.Modules included and Phrase learning screen with Listen and Record Options

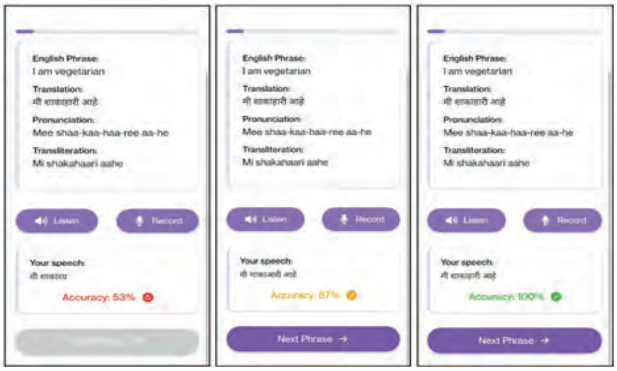

Fig. 3.Working of the Speech-To-Text feature

Figure 3. shows the implementation of the Speech-to-Text (STT) feature that permits users to practice their pronunciation by recording the voice of a given phrase. When a user activates the record function, their audio input is recorded and then passed through the Wav2Vec Automatic Speech Recognition (ASR) model-a leading-edge framework known for its accuracy and robustness under multilingual conditions. The transcription is then compared to the reference phrase using a Word Error Rate (WER) calculation that measures differences such as mispronunciations, insertions, and deletions. Based on the computed accuracy, the app provides immediate, color-coded feedback (green for high accuracy, orange for moderate, and red for low), allowing users to visually gauge their performance and identify areas for improvement.

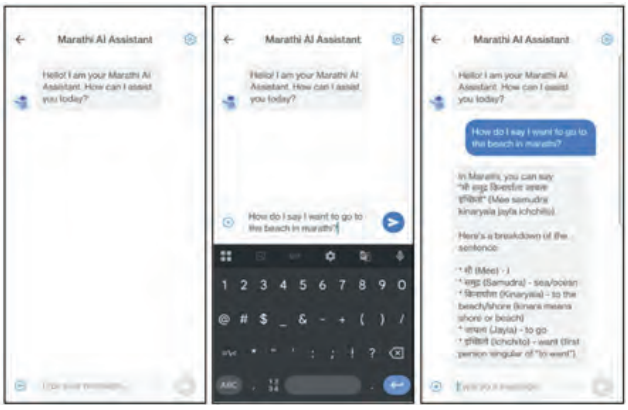

Fig. 4. AI Chatbot Assistant

Figure 4. presents the Marathi AI Assistant chatbot, an interactive tool designed to assist users with Marathi and English language queries, translations, and corrections. The chatbot offers a modern, conversational interface where users can input questions and receive contextual responses in real-time. It is built using the LangChain framework and powered by ChatGroq with the LLaMA 3–70B–8192 language model, enabling advanced natural language understanding and generation. Upon launching the chatbot, users are greeted by the assistant and invited to engage in dialogue, simulating a human-like conversational experience tailored for bilingual support.

Figure 5 depicts the Community Forum feature, which enables users to engage collaboratively in their Marathi language learning journey. Users can create or join topic-specific chat rooms focused on questions, interests, or challenges related to language acquisition.

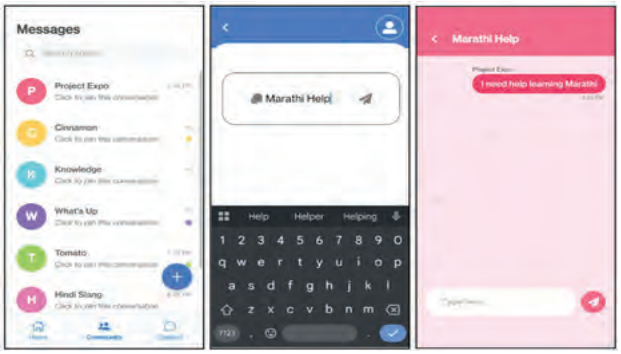

Fig. 5.Working of the Community Forum

These forums foster peer-to-peer support, allowing participants to exchange resources, clarify doubts, and discuss cultural nuances in a socially interactive environment. By connecting learners of varying proficiency levels, the feature encourages real-time collaboration, shared learning strategies, and mutual motivation. This community-driven structure transforms individual study into a dynamic, collective experience that enhances engagement, accelerates learning, and builds learner confidence.

RESULTS

The application was successfully developed by focusing on enhancing the user engagement and real-time Indian language practice through speech, text, and community interactions using Artificial Intelligence and Machine Learning by integrating multiple AI models.

The learning modules utilize sumedh/wav2vec2-large-xlsr-marathi model for speech-to-text and facebook/mms-tts-mar with VitsModel for text-to-speech. These allow users to listen to the right pronunciation of Marathi words and phrases, and then let them practice speaking the words with real-time transcription feedback based on how accurately they pronounce the words. Our initial

implementation showed a smooth integration of these models into the app's interface, and qualitative testing showed that the feedback loop (speak → get transcription → listen to correct pronunciation) worked reliably across various test phrases and modules.

A 24/7 conversational AI chatbot, built using Langchain and integrated with ChatGroq (llama3-70b-8192), was added to provide learners with an interactive assistant for practicing Marathi conversations and resolving doubts. The chatbot can answer grammar and vocabulary-related queries, provide sentence-level feedback, and simulate simple conversations in Marathi. It can handle basic contextual interactions and support common learner queries effectively.

The system includes a community feature, which provides users the ability to join or create their own chat rooms to interact with both other learners and native speakers. This was made as an intentional design choice to create a self-supported experience that mimics real-life language immersion. The design was made functional and then the interactions were tested for user flow: creating chat rooms, joining chat rooms, and basic moderation. All in all, the system has shown that it can be a viable system merging open source AI models and real-time interaction tools to create an accessible, Marathi-first language learning platform. No user study nor quantitative evaluation was conducted at this stage, but functional testing showed that all main features were functioning effectively for an iterative development cycle to be undertaken in subsequent stages, incorporating user feedback.

CONCLUSION AND FUTURE WORK

This application illustrated the idea of using AI technologies to offer the potential for an accessible and integrated Marathi language learning experience. The application uses models such as wav2vec2 for speech recognition, VitsModel for text-to-speech, and LLMs for conversational support. The application addressed the major issues with regional language learning, such as pronunciation, fluency, and continuous practice. After the experience learners can then engage in a community chat setting that allows for peer interaction in real time and simulate natural language immersion. It is important to note that the current implementation was focused on functionality and system stability, and the following iterations are planned to include comprehensive user testing, model-fine tuning to help accuracy, and additional features based on learner requirements. At its core, this research demonstrates the opportunities available to create scaled, AI-enhanced language learning tools for various underrepresented languages aimed at inclusion and preservation of languages digitally.

REFERENCES

1. J. K. Author, "Name of paper," Abbrev. Title of Periodical, vol. x, no. x, pp. xxx-xxx, Abbrev. Month, year, DOI. 10.1109.XXX.123456.
2. Wei, L. (2023). Artificial intelligence in language instruction: impact on English learning achievement, L2 motivation, and self-regulated learning. Frontiers in Psychology, 14. https://doi.org/10.3389/fpsyg.2023.1261955
3. TalkPal. (2023, March 29). The role of AI in language teaching and learning. Talkpal. https://talkpal.ai/the-role-of-ai-in-language-teaching-and-learning/
4. Acai Travel | Newsroom. (n.d.).https://www.acaitravel.com/blog/how-ai-is-breaking-language-barriers-and-expanding-horizons-for-travel-agencies
5. Nikhil. (2024, September 26). AI for Language Learning: A New Era in Language Acquisition. Exeed ECX. https://myexeed.com/ai-for-language-learning-a-new-era-in-language-acquisition/
6. Chen, Y. (2024). Enhancing Language acquisition: The role of AI in facilitating effective language learning. In Advances in Social Science, Education and Humanities Research/Advances in social science, education and humanities research (pp. 593–600). https://doi.org/10.2991/978-2-38476-253-8_71
7. Wodzak, S. (2024b, December 31). How Duolingo is using artificial intelligence for social good. Duolingo Blog. https://blog.duolingo.com/ai-improves-education/
8. Vesselinov, R., PhD, Grego, J., PhD, & Research Team. (2016). The busuu Efficacy Study. In The Busuu Efficacy Study (p. 1). http://comparelanguageapps.com/documentation/The_busuu_Study2016.pdf
9. Abarghoui, M. A., & Taki, S. (2018). Measuring the Effectiveness of using "Memrise" on High school Students' Perceptions of Learning EFL. Theory and Practice in Language Studies, 8(12), 1758. https://doi.org/10.17507/tpls.0812.25
10. Baevski, A., Zhou, H., Mohamed, A., & Auli, M. (2020, June 20). wav2vec 2.0: A Framework for Self-Supervised Learning of Speech Representations. arXiv.org. https://arxiv.org/abs/2006.11477
11. Heath, A. (2024, April 18). Meta's battle with ChatGPT begins now. The Verge. https://www.theverge.com/2024/4/18/24133808/meta-ai-assistant-llama-3-chatgpt-openai-rival
12. TalkPal, Inc. (2025, April 15). AI-Assisted Language Learning - TalkPal. Talkpal. https://talkpal.ai/learn-languages-with-ai/

Gradient-Based Meta-Learning for Temporal Data: A Study of MAML and Reptile

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ABSTRACT

This paper explores the application of a gradient-based meta-learning framework for stock price prediction. We evaluated the performance of Model-Agnostic Meta-Learning(MAML) and the Reptile framework in conjunction with Long Short-Term Memory (LSTM) and Feed Forward Neural Network (FFNN) architectures. This models are trained and tested on historical stock price data (2010-2021) of TCS stock, and their performance is benchmarked against traditional time series forecasting methods like AutoRegressive Integrated Moving Average (ARIMA), Seasonal AutoRegressive Integrated Moving Average (SARIMA), Error-Trend-Seasonality (ETS), and Simple Exponential Smoothing (SES). The results indicate that MAML, particularly when combined with LSTM networks base model, gives good performance in capturing the non-linear dynamics of stock prices. Also it exhibits a progressive improvement in performance with increasing iterations and exhibits a strong model fit. On the other hand, Reptile with LSTM shows diminishing returns with further iterations. Furthermore, LSTM-based models give better results when compared with FFNN-based models, highlighting the importance of capturing temporal dependencies in time series forecasting. Notably, both meta-learning algorithms give us better results than classical time series forecasting methods. This research suggests that meta-learning, especially MAML with LSTM, gives a promising avenue for enhancing the accuracy and adaptability of stock price prediction models.

***KEYWORDS** : Meta-learning, Time series forecasting, MAML, Reptile, LSTM, FFNN, Stock price prediction*

INTRODUCTION

Predicting stock price accurately is one of the difficult yet important tasks in the domain of finance with significant implications for investment strategies, risk management and economic forecasting. The difficult to predict and non-stationary nature(conditions) of stock markets characterized by volatility and susceptibility to various economic and geopolitical factors makes the prediction difficult. Classical time series forecasting methods mostly struggle to capture these hidden complexities which necessitate the exploration of various advanced machine learning techniques.

In recent years, use of meta-learning framework has emerged as an excellent approach for solving various challenges of time series forecasting. Unlike classical machine learning models which need to learn from scratch on each new task, use of meta-learning enables models to learn how to learn while allowing them for rapid adaptation to new tasks with limited amounts of data. This capability is particularly useful to stock price prediction, where it is necessary that models must quickly adapt to evolving market conditions.

This study investigates the application of two gradient-based meta-learning algorithms i.e. Model-Agnostic Meta-Learning (MAML) and Reptile for the problem of stock price prediction which is one of the applications of time series forecasting. MAML aims to learn a set of initial model parameters that can be quickly adapted to new tasks with a less number of gradient steps, on the other hand Reptile seeks to find an initialization that is close to the parameters of several task-specific networks. The findings of this paper have the potential to contribute to the

development of more accurate and adaptable stock price prediction models, which could possibly benefit investors, financial institutions, and policymakers.

The objectives of this research are to:

1. Evaluate the effectiveness of gradient-based meta-learning algorithms i.e. MAML and Reptile, for stock price prediction, one of the applications of time series forecasting.
2. Compare the performance of MAML and Reptile algorithms in conjunction with Long Short-Term Memory (LSTM) network and Feed Forward Neural Network(FFNN) as base models.
3. Benchmark the performance of meta-learning-based models against classical time series forecasting methods which includes AutoRegressive Integrated Moving Average (ARIMA), Seasonal AutoRegressive Integrated Moving Average (SARIMA), Error-Trend-Seasonality (ETS), and Simple Exponential Smoothing (SES).
4. Give insights into the applicability of meta-learning framework for enhancing the accuracy and adaptability of stock price prediction models or problems.

The Contribution of this work are listed below:

1. We provide a systematic comparative analysis of two prominent gradient-based meta-learning algorithms i.e. MAML and Reptile in the context of stock price prediction. This study highlights the pros and cons of each algorithm for this specific time series forecasting task or problem.
2. We evaluate the effectiveness of combining MAML and Reptile with two different neural network base models i.e. LSTM and FFNN. This investigation explains the importance of the base model architecture in the performance of meta-learning framework for time series data or problems.
3. We benchmark the performance of meta-learning-based models against classical time series forecasting methods which includes ARIMA, SARIMA, ETS and SES to provide a comprehensive study of their effectiveness in stock price prediction.
4. This research contributes to the understanding of how meta-learning frameworks can be effectively applied to stock price prediction while offering insights into the selection of appropriate or correct meta-learning algorithms as well as base model architectures.

LITERATURE ANALYSIS

The increasing interest in applying meta-learning algorithms for time series forecasting problems stems from their ability to adapt to new tasks with limited amounts of data, leveraging prior experiences to enhance predictions in domains including stock markets [1, 2]. Samanta et al. [1] introduced the Meta-Cognition Fuzzy Inference System (MCRTFIS-MN) which demonstrates improved efficiency and accuracy in fuzzy systems through one-shot learning. Addressing the various challenges of accuracy and hyperparameter optimization, Li et al. [2] implements a hybrid model that decomposes time series data into linear and non-linear components, utilizing Gradient-based least mean square (GD-LMS) for linear patterns on the other hand an ISSA-optimized LSTM for non-linear aspect which results in enhanced forecasting accuracy. Similarly, Mu et al. [3] developed the MS-SSA-LSTM model for the problem of stock price prediction which integrates sentiment analysis and optimizes LSTM hyperparameters with the Sparrow Search Algorithm to achieve better predictive accuracy, specifically in volatile market conditions. Elgamal et al. [4] made the Reptile Search Algorithm (RSA) better by including chaos theory and simulated annealing to improve its search capabilities. Terence L et al. [5] explored model fusion in forecasting, proposing the Deep-learning FORecast Model Averaging (DEFORMA) model that combines multiple meta-learning approaches and achieved superior performance in the M4 competition. MAML algorithm which was developed by Finn et al. [12] offers a versatile approach for fast adaptation in various learning tasks which also includes time series prediction. Nichol et al. [13] further explored first-order meta-learning algorithms like Reptile, offering computational advantages. Hospedales et al. [6] gives a comprehensive overview of the meta-learning field and its future potential in time series forecasting. Finally, Chang et al. [8] presented stock price prediction using a meta-learning algorithm with various Convolutional Neural Network (CNN) base models and a novel labeling method.

Existing research in meta-learning for temporal data, while promising, presents several limitations that motivate our study. Firstly, a direct comparative analysis of prominent gradient-based meta-learning algorithms like MAML and Reptile specifically for time series forecasting tasks, such as stock price prediction, remains relatively underexplored. While individual studies exist, a clear understanding of their respective strengths and weaknesses in this context is lacking. Secondly, the interplay between different base model architectures and these meta-learning

algorithms for temporal data has not been systematically evaluated. Understanding which model best leverages the rapid adaptation capabilities of MAML and Reptile is crucial for effective application. Furthermore, many meta-learning studies lack proper benchmarking against well-established traditional time series forecasting methods which makes it challenging to assess the real-world utility of these advanced techniques. Finally, while some works have touched upon meta-learning for stock price prediction, deeper insights into the specific conditions and model choices that yield significant improvements are still needed.

METHODOLOGY

We utilize MAML [12] and Reptile [13] as meta-learning strategies for improving the adaptability of forecasting models on time series data.

MAML learns a model initialization that quickly adapts to new tasks using a few gradient descent steps. It consists of:

Inner update (task-specific):

$$\theta' = \theta - a \nabla \ L(f\_\theta) \quad (1)$$

Meta update (across tasks):

$$\theta \leftarrow \theta - b \sum \nabla\_\theta \, L(f\_\theta') \quad (2)$$

In equation (1), a is the inner-loop learning rate and in equation (2), b is the meta-learning rate.

Reptile simplifies meta-learning by avoiding second-order derivatives. It updates the initialization as:

Update rule:

$$\theta \leftarrow \theta + \varepsilon (\theta' - \theta) \quad (3)$$

In equation (3), θ' is the model parameter after training on a task, and ε is the step size.

Dataset Creation: The preprocessed data was structured into a dataset suitable for time series analysis.

Data Splitting: The dataset was divided into two halves one for training and other for testing in 80:20 ratio.

Tensor Conversion: The data was converted into tensor format so that it would be compatible with the neural network models.

Model Definition: Two neural network architectures were used as base models:

LSTM Network: LSTM networks work effectively with time series data due to their ability to capture temporal dependencies.

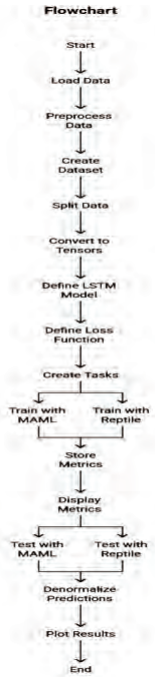

Fig. 1: Methodology/Flowchart

FFNN: FFNNs were used to provide a comparison with a non-sequential model to make investigation better.

Loss Function Definition: A suitable loss function (e.g., Mean Squared Error) was defined to quantify the difference between predicted and actual stock prices.

Meta-Learning Algorithm Implementation: Two gradient-based meta-learning algorithms were implemented:

MAML:MAML was used as a meta learning framework to train both the LSTM and FFNN base models.

Reptile: Reptile another meta-learning framework used to train the LSTM and FFNN base models.

Training and Evaluation: The LSTM and FFNN models were trained using both MAML and Reptile. The performance of trained models was then evaluated on the test dataset using various evaluation metrics like Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and R-squared (R2).

Denormalization: Predictions were denormalized to the original scale of the stock price data.

Results Visualization: The predicted stock prices of tcs stock were plotted against the actual prices of tcs stock to visualise the model performance.

RESULTS AND DISCUSSION

Our investigation into the use of gradient-based meta-learning algorithms i.e. MAML and Reptile, for temporal stock price prediction using LSTM and FFNN as base models, give us several important findings. We evaluated model performance across 100 iterations using RMSE, MAE, and R2, also compared these meta-learning approaches with classical time series forecasting methods i.e. ARIMA, SARIMA, ETS and SES.

Table 1: MAML Evaluation Metrics over Iterations with LSTM

Iteration	RMSE	MAE	R^2
10	529.38	408.43	0.178
20	337.04	258.21	0.667
30	281.51	211.91	0.767
40	699.47	529.69	-0.43
50	231.62	167.52	0.84
60	454.91	413.92	0.39
70	370.86	315.22	0.60
80	225.79	173.39	0.85
90	299.39	221.07	0.73
100	207.06	147.22	0.87

Meta-Learning Models: LSTM Performance

The LSTM-based models demonstrated a superior capacity to capture the non-linear dynamics of stock price movements compared to FFNNs and traditional methods. MAML with LSTM exhibited a progressive improvement in performance with increasing iterations. The R2 value reached 0.87 at iteration 100, showing a strong model fit and a substantial improvement in the model's ability which explain the variance in stock prices, as detailed in Table 1. This suggests that MAML effectively optimizes the LSTM's initial parameters, enabling the LSTM to rapidly adapt to new stock price patterns. The corresponding decrease in RMSE and MAE further corroborates this enhanced predictive accuracy.

Table 2: Reptile Evaluation Metrics over Iterations with LSTM

Iteration	RMSE	MAE	R^2
10	214.44	162.03	0.86
20	250.27	200.79	0.81
30	282.17	231.94	0.76
40	304.36	253.56	0.72
50	338.17	283.09	0.664
60	346.61	290.40	0.64
70	352.75	295.00	0.63
80	300.71	251.56	0.73
90	419.25	351.35	0.48
100	415.82	353.32	0.49

Reptile with LSTM, while demonstrating a high initial performance (R2 of 0.86 at iteration 10) showed diminishing returns with further iterations. The R2 value declined to 0.49 by iteration 100, as shown in Table 2. This suggests that while Reptile enables the LSTM to quickly learn a reasonable representation of the data, it may converge to a suboptimal solution, limiting its capacity to benefit from prolonged training in this context. The visual representation of LSTM performance can be seen in "Figure 2".

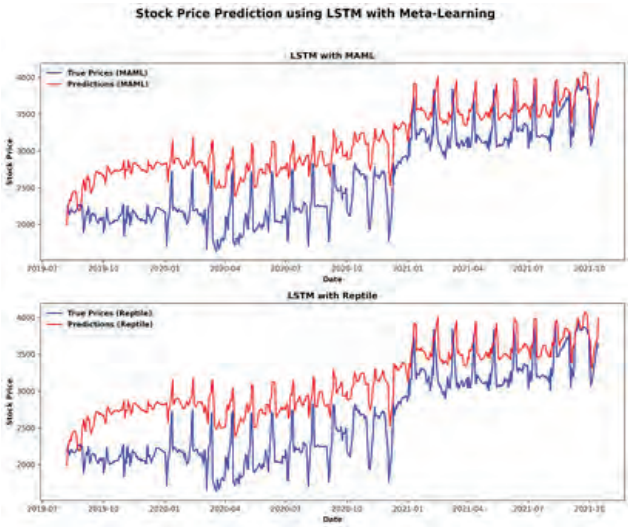

Fig. 2: MAML and Reptile with LSTM

Meta-Learning Models: FFNN Performance

In contrast to the LSTM model, FFNN-based models showed relatively stable performance across iterations. MAML with FFNN exhibited an R2 of around 0.72-0.79, while Reptile with FFNN maintained an R2 value of approximately 0.75, as shown in Tables 3 and 4, respectively. This suggests that while meta-learning facilitates the learning of a functional mapping between input and output, the FFNN architecture may lack the inherent capacity to fully capture the temporal dependencies present in the stock price data, even with the optimized initial parameters provided by MAML and Reptile. The performance of FFNN can be seen in "Figure 3".

Table 3: MAML Evaluation Metrics over Iterations with FFNN

Iteration	RMSE	MAE	R^2
10	287.17	212.64	0.76
20	269.91	218.48	0.79
30	299.39	248.68	0.74
40	297.95	247.85	0.74
50	301.61	251.90	0.73
60	303.76	254.98	0.73
70	300.48	251.76	0.73
80	306.95	257.88	0.72
90	288.87	238.54	0.76
100	291.51	243.22	0.75

Table 4: Reptile Evaluation Metrics over Iterations with FFNN

Iteration	RMSE	MAE	R^2
10	291.51	243.22	0.75
20	291.51	243.22	0.75
30	291.51	243.22	0.75
40	291.52	243.22	0.75
50	291.52	243.22	0.75
60	291.52	243.22	0.75
70	291.52	243.23	0.75
80	291.52	243.23	0.75
90	291.53	243.23	0.75
100	291.53	243.24	0.75

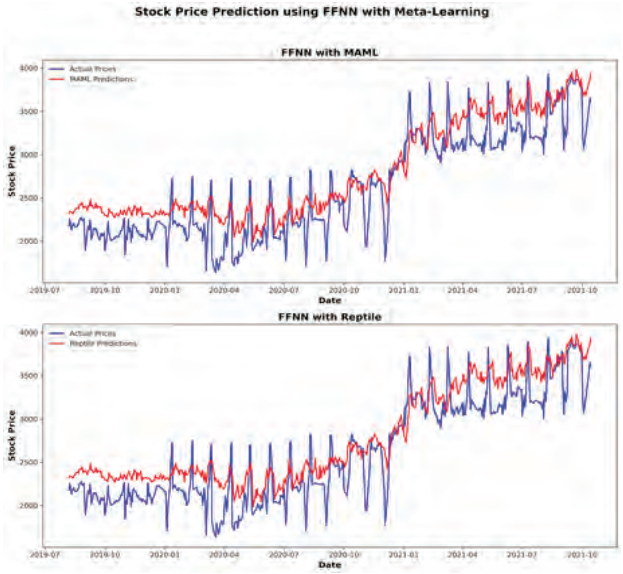

Fig. 3: MAML and Reptile with FFNN

Comparison with Traditional Methods

The classical time series forecasting methods i.e. ARIMA, SARIMA, ETS and SES demonstrated limited success in accurately predicting stock price fluctuations. As illustrated in "Figure 4", these models produced relatively flat predictions that failed to capture the significant upward and downward trends characteristic of stock market behavior. This indicates that these traditional methods are less suitable for modeling the non-stationary and volatile nature of stock price data.

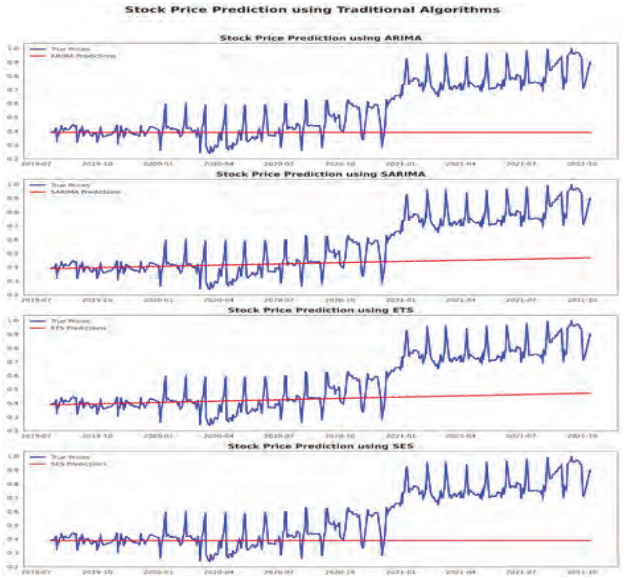

Fig. 4: Traditional Forecasting Models

Discussion:The results highlight the potential of meta-learning, particularly MAML with LSTM, for enhancing the accuracy and adaptability of stock price prediction models. The ability of MAML to learn an effective initialization that enables fast adaptation to new stock price sequences is a key advantage as demonstrated by the improved R2 values in Table 1. The superior performance of LSTM over FFNN underscores the importance of the base model's capacity to capture temporal dependencies.

The contrasting performance of MAML and Reptile with LSTM suggests that while both algorithms can improve learning, they exhibit different convergence behaviors. MAML appears to be more effective in optimizing LSTM performance over extended training, potentially due to its second-order optimization approach, which may lead to a more refined solution. Reptile, with its simpler first-order approach, achieves a reasonable initial performance but may be more prone to converging to a local optimum.

The poor performance of traditional time series methods in this study aligns with the understanding that stock prices are influenced by a multitude of factors, leading to non-stationary and unpredictable patterns that these methods struggle to model, as shown in "Figure 4.

CONCLUSION

This study demonstrates that gradient-based meta-learning algorithms, particularly MAML, significantly enhances the accuracy and adaptability of stock price prediction models. Among the evaluated models, MAML combined with LSTM consistently outperformed other configurations, effectively capturing temporal dependencies and exhibiting improved performance with increased iterations. Reptile on the other hand is computationally efficient and showed diminishing gains over time especially with LSTM. Furthermore, LSTM-based architectures give better results than FFNNs in modeling temporal patterns, reinforcing the importance of sequence-aware models in time series forecasting. When benchmarked against traditional forecasting techniques like ARIMA, SARIMA, ETS and SES, both MAML and Reptile yielded superior predictive performance while highlighting the potential of meta-learning as a robust alternative for financial time series prediction. Overall, the findings suggest that MAML, in conjunction with LSTM, offers a powerful and generalizable framework for adaptive and accurate stock market forecasting. In future studies, we plan to extend this research in several directions. First, we aim to evaluate the performance of the proposed meta-learning framework in this paper on different stocks, including Grasim, Tata Steel, and the Dow Jones U.S. Stock Index, to assess its generalizability across various market conditions. Second, we intend to explore the use of Gated Recurrent Units (GRUs) as an alternative base model architecture, given their efficiency and effectiveness in capturing sequential dependencies. These extensions will further validate the potential of meta-learning for enhancing time series prediction and broaden the applicability of our findings.

REFERENCES

1. Subhrajit Samanta,Shubhangi Ghosh,Suresh Sundaram,"A Meta-cognitive Recurrent Fuzzy Inference Systemwith Memory Neurons (McRFIS-MN) and its Fast Learning Algorithm for Time Series Forecasting",IEEE Symposium Series on Computational Intelligence SSCI 2018.
2. P. H. Li, D. X. Chen, H. Y. Huang, X. T. Wu, H. W. Jiang and G. L. Ji, "A Novel Hybrid Scheme for Time Series Prediction Using LMS Filter and ISSA-based LSTM," 2022 IEEE Smartworld, Ubiquitous Intelligence Computing, Scalable Computing Communications, Digital Twin, Privacy Computing, Metaverse, Autonomous Trusted Vehicles (SmartWorld/UIC/ScalCom/DigitalTwin/PriComp/Meta), Haikou,China, 2022,pp.343-350,doi:10.1109/SmartWorld-UIC-ATC-ScalCom-DigitalTwin-
2. PriComp-Metaverse56740.2022.00070.
3. G. Mu, N. Gao, Y. Wang and L. Dai, "A Stock Price Prediction Model Based onInvestor Sentiment and Optimized Deep Learning," in IEEE Access, vol. 11, pp. 51353-1367, 2023, doi: 10.1109/ACCESS.2023.3278790.
4. Z. Elgamal, A. Q. M. Sabri, M. Tubishat, D. Tbaishat, S. N. Makhadmeh and O. A.Alomari, "Improved Reptile Search Optimization Algorithm Using Chaotic Map and Simulated Annealing for Feature Selection in Medical Field," in IEEE Access, vol. 10, pp. 51428-51446, 2022, doi: 10.1109/ACCESS.2022.3174854.
5. Terence L. van Zyl,"Late Meta-learning Fusion Using Representation Learning for Time Series Forecasting", https://doi.org/10.48550/arXiv.2303.11000
6. Timothy Hospedales , Antreas Antoniou, Paul Micaelli, and Amos Storkey,"Meta-Learning in Neural Networks: A Survey",IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 44, NO. 9, SEPTEMBER 2022.
7. Xiao Yao,Jianlong Zhu,Guanying Huo, Ning Xu, Xiaofeng Liu, Ce Zhang,"Model-agnostic multi-stage loss optimization meta learning",International Journal of Machine Learning and Cybernetics (2021) 12:2349–2363 https://doi.org/10.1007/s13042-021-01316-6 ,2021.
8. Shin-Hung Chang, Cheng-Wen Hsu, Hsing-Ying Li, Wei-Sheng Zeng and Jan-Ming Ho,"Short-Term Stock Price-Trend Prediction Using Meta-Learni ng",978-1-6654-4207-7/21,2021
9. Yanbing Song,Shaofei Zang,Jianwei ma,Huimin Li,Jinfeng Lv,"Stock prediction based on Weighted meta extreme learning machine",979-8-3503-7922-8/24,2024
10. M. Maya, W. Yu and X. Li, "Time series forecasting with missing data using neural network and meta-transfer learning," 2021 IEEE Symposium Series on Computational Intelligence (SSCI), Orlando, FL, USA, 2021, pp. 1-6, doi:10.1109/SSCI50451.2021.9659864.
11. X. Wen and W. Li, "Time Series Prediction Based on LSTM-Attention-LSTM Model," in IEEE Access, vol. 11, pp. 48322-48331, 2023, doi: 10.1109/ACCESS.2023.3276628.
12. Chelsea Finn, Pieter Abbeel, and Sergey Levine. . "Model-agnostic meta-learning for fast adaptation of deep networks" In Proceedings of the 34th International Conference on Machine Learning - Volume 70 (ICML'17). JMLR.org, 1126–1135,2017.
13. Nichol, Alex, Joshua Achiam and John Schulman. "On First-Order Meta-Learning Algorithms." ArXiv abs/1803.02999 (2018): n. pag.

Handwritten Character Generation Using Generative Adversarial Networks (GANs)

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ABSTRACT

In this paper, we examine how to develop realistic-looking handwritten letters and numbers using Generative Adversarial Networks (GANs). To produce clear and visually compelling outputs, we suggest a model based on WGAN-GP, a stable variant of GANs. Our technology can produce particular characters or numbers as required by enabling user-defined character inputs. This study not only shows a high model performance, but also suggests real-world applications in digital document design, education, and automated writing systems.

***KEYWORDS** : Handwritten character generation, Generative adversarial networks, Handwriting synthesis, Deep learning, Image generation, Neural networks, Character recognition.*

INTRODUCTION

Even in the modern digital era, handwriting is still a crucial means of expressing language and emotion. However, employing technology to recreate handwriting is a challenging undertaking. We now have more effective techniques to address this thanks to developments in deep learning, particularly GANs.Our project's main goal is to create a handwriting generation model by utilizing WGAN-GP, a particular type of GAN. The primary advantages of WGAN-GP over conventional GANs are enhanced training stability and the avoidance of typical problems like mode collapse.

Our system's usage of class labels, which enable the model to produce a user-specified character or number, is another important component. Our main goals are to create a model that can generate handwritten characters that look natural, evaluate the generated characters for stylistic diversity and visual accuracy, and determine possible uses and future possibilities for this technology. This finding is significant because it creates opportunities for automating handwriting-dependent tasks, such creating personalized typefaces or instructional materials for handwriting practice.

Generative Adversarial Networks (GANs)

In 2014, Ian Goodfellow introduced Generative Adversarial Networks. The Generator and the Discriminator are the two models used in these networks. While the Discriminator learns to discern between produced and actual data, the Generator fabricates phony data in an attempt to replicate real data. In a sort of game, both models get better together, increasing the realism of the product that is produced.

The following is the definition of the standard GAN objective function:

$$\mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))] = \min_G \max_D V(D,G)$$

where - z represents random noise vectors sampled from a latent space pz(z), - x represents real data samples taken from the data distribution p(x), - G(z) is the Generator's output, and - D(x) is the Discriminator's output probability that x is real.

Wasserstein GAN with Gradient Penalty (WGAN-GP)

Although GANs have shown promise, training stability

is a common problem. The Wasserstein GAN, often known as the WGAN, produces more stable gradients by altering the way the distinctions between actual and false data are quantified. This is furthered by WGAN-GP, which uses a gradient penalty to maintain a dependable and seamless training process.

The formula for the WGAN objective function is

$$\min_G \max_D \mathbb{E}_{x\sim p_{\text{data}}(x)}[D(x)] - \mathbb{E}_{z\sim p_z(z)}[D(G(z))]$$

WGAN-GP adds a gradient penalty term to enforce the Lipschitz restriction that the Wasserstein distance demands:

$$\mathcal{L}_{\text{GP}} = \lambda \mathbb{E}_{\hat{x}\sim p_{\hat{x}}}\left[(\|\nabla_{\hat{x}} D(\hat{x})\|_2 - 1)^2\right]$$

where -λ is the gradient penalty coefficient and -x̂ is a randomly interpolated sample between actual and false data.

Both terms are combined in the final WGAN-GP loss function:

$$\mathcal{L} = \mathbb{E}_{x\sim p_{\text{data}}(x)}[D(x)] - \mathbb{E}_{z\sim p_z(z)}[D(G(z))] + \mathcal{L}_{\text{GP}}$$

Conditional GANs

An enhanced kind of GANs is called a conditional GAN, in which we provide the model with certain instructions, such as a label or a description. This enables us to regulate the type of output we desire. To increase the model's versatility, we employ class labels in this study to instruct the Generator on which particular character to generate.

LITERATURE ANALYSIS

Paper	Methodology	Observation	Limitations	Future Scope
[1] E. Alonso and associates, 2019	The features of the augmented conditional GAN include bi-LSTM embedding, CRNN for recognition, generator with up-sampling ResBlocks, Conditional Batch Normalization (CBN), and self-attention; discriminator with down-sampling ResBlocks; adversarial (hinge), CTC, and λ=1 for gradient balancing.	Fixed dimensions, variable-length words, some style collapse, and French and Arabic datasets were used for testing; synthetic data enhanced Handwritten Text Recognition (HTR).	Collapsed style, fixed image size.	Increase the variety of styles and accommodate different dimensions.
[2] S. Fogel et al., 2020	ScrabbleGAN: semi-supervised, balanced adversarial and CTC losses; character filter embedding; convolutional up-sampling generator; residual block discriminator; CRNN recognizer.	Improved HTR Word Error Rate (WER) and Normalized Edit Distance (NED), reduced artifacts compared to [1], improved Fréchet Inception Distance (FID) and Geometry Score (GS), and the capacity to produce zero-shots in a variety of languages.	High memory requirements and computational complexity.	Increase productivity and accommodate bigger character sets.
[3] J. Zdenek and H. Nakayama, 2021	JokerGAN: text line awareness through text line embedding (TLE), variable-length character sequences, and multi-class conditional batch normalization.	Large character sets (like Japanese) can be handled with less memory utilization, and character alignment is enhanced.	Sometimes overlook minute details in style.	Improve text line consistency and style capture.
[4] X. Liu et al., 2021	HTG-GAN: style discriminator, generator, and encoder with residual blocks; losses: reconstruction, adversarial, CTC, and KL divergence.	Metrically comparable to [1] and [2]; modest HTR improvement, reduced artifacts, and improved visual quality.	Restricted to certain styles, inadequate generality.	Increase the variety of styles and enhance generalization.

[5] L. Kang et al., 2020	Fully connected layer embedding, Adaptive Instance Normalization (AdaIN), discriminator with residual blocks, VGG-19-BN, and B-GRU recognizer are all components of GANwriting; losses include binary cross-entropy, multi-class cross-entropy, and KL divergence.	Outperformed FUNIT; few-shot setup, human-satisfactory, limited to less than 10 letters, and worsened on out-of-vocabulary (OOV) terms.	OOV problems, short word limit.	Improve OOV performance and accommodate lengthier messages.
[6] J. Gan and W. Wang, 2021	With two adversarial losses and balanced objective weights, HiGAN is comparable to GANwriting.	In terms of visual quality and HTR metrics, it is better than [2] and [5]; it can handle lengthy paragraphs and leaves off spaces.	Errors in punctuation and lack of spaces.	Enhance the text's structure by adding punctuation and spacing.
[7] B. Davis et al., 2020	TS-GAN: modified gradient balancing, perceptual loss encoder, spacing network, and coupled GAN and auto-encoder training.	Comparable FID and GS to [2]; convincing pictures that deceived people through Amazon.	Style clustering reduces diversity.	Author-level style clustering using Mechanical Turk.
[8] J. Gan et al., 2022	HiGAN+: gradient balancing, three-stage training, patch discriminator, adjusted losses, and character embeddings.	Visually and numerically outperformed [3], [5], [6], and [7]; human-preferred, but had trouble with numerals, punctuation, and scrawled text.	Fails on numbers, punctuation, and scrawled writing.	Enhance the way that numerals, punctuation, and handwritten text are handled.
[9] Y. Luo et al., 2022	SLOGAN: dual-head discriminators (D_char, D_join), encoder-decoder generator, style bank lookup table, parameterized styles, printed picture input, and no recognizer.	outperformed [1], [2], and [5] on metrics; slight style imitation and output confusion caused by people.	Imitation in the subtle manner is inaccurate.	Improve style precision and accommodate intricate styles.
[10] Y. Wang et al., 2019	HWGANs: CNN-LSTM discriminator with recurrent latent variable model generator and Path Signature Features (PSF).	writing that is more realistic and natural than that produced by non-GAN generators.	restricted to stroke data rather than complete images.	Extend to full image generation, enhance realism.
[11] C. Chang et al., 2020	Cross-lingual zero-shot GAN, extended ScrabbleGAN for multilingual text generation.	Enabled generation in multiple languages without language-specific training.	Inaccurate language-specific style capture.	Improve language-specific styles, expand language support.
[12] L. Wang et al., 2021	Transfer of multi-scale styles By utilizing adaptive feature fusion (AFF), GAN expands upon GANwriting.	Enhanced style transfer and produced text with a variety of style scales.	Computationally demanding.	Increase productivity and improve the accuracy of style transfer.

METHODOLOGY

Dataset Description

A Kaggle dataset containing handwritten pictures of capital and lowercase English letters (A-Z, a-z) and numbers (0–9) was utilized. The dataset provides a strong foundation for training the model because it includes a range of handwriting styles. All 10 numerals and all capital and lowercase characters are represented by its 62 classes. After converting each image from grayscale to RGB format and resizing it to 64x64 pixels, the pixel values were normalized to fall between -1 and 1. 20% of the data was used for testing, while the remaining 80% was used for training. This

configuration ensures that the model receives consistent input and functions well across a variety of styles.

Model Architecture

The Generator and the Discriminator are the two main parts of the WGAN-GP configuration that we employed. Class labels are used to improve both sections.

Generator

A random noise vector and a character label are sent into the generator, which initially uses an embedding layer to turn them into a dense vector. After concatenating this embedded label with the noise vector, the input is passed through many layers that progressively upsample it to create an image. The last layer scales pixel values into the appropriate range using a Tanh activation function.

Among the Generator's primary features are: - Input: An embedding vector that represents the class label concatenated with a random noise vector $z \in \mathbb{R}100$. Class labels are mapped to a dense vector of size 256 by the embedding layer, which then concatenates it with the noise vector. The architecture consists of transposed convolutional layers with ReLU activations and batch normalization. The last layer generates pixel values in the [−1,1] range by using a Tanh activation.

The Generator architecture is summarized below:

Layer Type	Output Shape	Parameters
Input (Noise + Embedding)	1 × 100 + 256	N/A
Transposed Convolution	4 × 4 × 1024	Kernel Size: 4, Stride: 1
Transposed Convolution	8 × 8 × 512	Kernel Size: 4, Stride: 2
Transposed Convolution	16 × 16 × 256	Kernel Size: 4, Stride: 2
Transposed Convolution	32 × 32 × 128	Kernel Size: 4, Stride: 2
Transposed Convolution	64 × 64 × 3	Kernel Size: 4, Stride: 2

Discriminator

Both authentic and fraudulent images are accepted by the discriminator, along with the label that goes with them. To fit the image's proportions, the label is altered and embedded. Normalization and LeakyReLU activation functions are then applied to each convolutional layer once this reshaped label has been concatenated with the picture data. One numerical value that indicates whether the input image is produced or most likely real is the final output.

The following is a summary of the discriminator architecture:

Layer Type	Output Shape	Parameters
Input (Image + Embedding)	64 × 64 × 4	N/A
Convolution	32 × 32 × 64	Kernel Size: 4, Stride: 2
Convolution	16 × 16 × 128	Kernel Size: 4, Stride: 2
Convolution	8 × 8 × 256	Kernel Size: 4, Stride: 2
Convolution	4 × 4 × 512	Kernel Size: 4, Stride: 2
Convolution	1 × 1 × 1	Kernel Size: 4, Stride: 1

Training Procedure

Our training regimen was consistent and alternated between upgrading the Generator and the discriminator. To keep things in balance, the Discriminator is updated five times for each Generator update. We trained the model for 100 epochs with a batch size of 64 and a learning rate of 0.00005. With each Generator upgrade, the Discriminator—also known as the Critic—was changed five times. To enforce stability, we applied a gradient penalty with a coefficient of 10 to make sure the model complies with Lipschitz continuity, a crucial idea in WGANs for stable training.

$$\mathcal{L}_D = \mathbb{E}[D(x)] - \mathbb{E}[D(G(z))] + \lambda \cdot \mathcal{L}_{\text{GP}}$$

$\mathscr{L}$GP is the definition of this loss, and the discriminator parameters are modified appropriately. After that, a batch of phony photos is created and the adversarial loss $\mathscr{L}G = -\mathbb{E}[D(G(z))]$ is minimized, which encourages the Generator to generate outputs that the discriminator is unable to discern from actual data. By interpolating between genuine and fake pictures and measuring the gradient norm's divergence from 1, the gradient penalty $\mathscr{L}$GP is calculated. With a batch size of 64 and a learning rate of 5×10^{-5}, the training is carried out over 100 epochs. Additionally, the gradient penalty coefficient

λ is set at 10 and the Discriminator (also known as the Critic) is updated five times for every Generator update.

The following are some of the training hyperparameters: 64-person batch; 5 × 10−5 learning rate There are one hundred epochs. The gradient penalty coefficient (λ) is 10. Each generator update requires five critical iterations.

Losses were calculated using the Wasserstein formula, which preserves training stability and improves gradient behavior. We also included a gradient penalty to ensure that the model complies with Lipschitz continuity, a mathematical condition that ensures stability.

Evaluation Metrics

Our evaluation of the model was done in two main ways. We used qualitative evaluation by first visually checking the generated images for clarity, realism, and stylistic coherence. Second, we used quantitative metrics: Fréchet Inception Distance (FID), which compares the distribution of generated images to real ones (lower is better), and Inception Score (IS), which measures the clarity and diversity of the generated images (higher is better). We also produced words like "HELLO" and "World" to evaluate the model's ability to maintain consistent handwriting styles across sequences.

RESULTS AND DISCUSSION

Qualitative Results

The produced characters appear incredibly lifelike due to their clear outlines and appropriate spacing. Characters like "A" and "G" displayed pronounced loops and curves. Each letter of a phrase, such as "HELLO," followed the same handwriting style, which is crucial for tasks like automatic handwriting translation.

Individual Character Generation

High scores were obtained via the model's analysis. A Fréchet Inception Distance (FID) of 18.7 demonstrated the high degree of similarity between the generated and actual images. Furthermore, the outputs showed a high balance between diversity and clarity, as evidenced by their Inception Score (IS) of 3.85. These numbers are reasonably competitive when compared to other GAN-based handwriting models.

Word Generation

Word-forming character sequences can be produced by the model. For instance, all of the characters in the word "HELLO" (Figure 2) have handwriting styles that are consistent and resemble those of a human.

Quantitative Results

We assessed the model using two commonly used measures, Fréchet Inception Distance (FID) and Inception Score (IS), to supplement the qualitative study.

Fréchet Inception Distance (FID)

The degree of resemblance between the distribution of generated and real images is measured by the FID score. Better alignment between the two distributions is indicated by a lower FID score. With a FID score of 18.7, our model can compete with the most advanced GAN-based handwriting synthesis models.

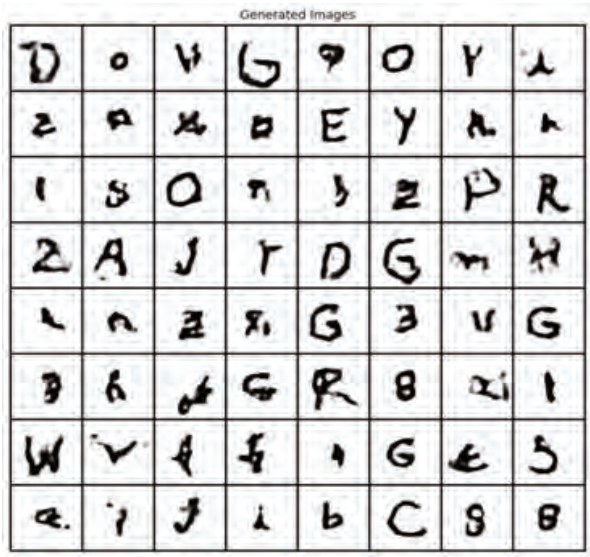

Fig. 1: Generated Characters

Fig. 2: Generated "HELLO"

Similarly, the word "World" (Figure 3) showcases the model's ability to handle mixed-case inputs and maintain stylistic coherence.

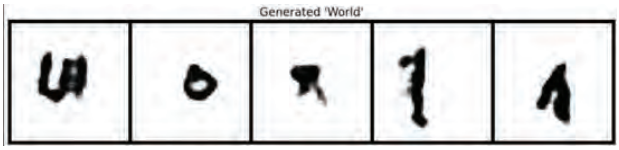

Fig. 3: Generated "World"

Inception Score (IS)

The diversity and quality of the generated images are assessed by the Inception Score. Better performance is indicated by a greater IS. The variety and clarity of the generated characters are reflected in our model's IS of 3.85.

Table 1: Formula Metric

Metric	Value
Fréchet Inception Distance (FID)	18.7
Inception Score (IS)	3.85

RESULTS AND DISCUSSION

The model's output quality is further strengthened by its exceptional ability to produce characters that appear amazingly realistic and human. Its usefulness for targeted creation is further increased by the precise control over the character that is formed, which is made possible by the successful implementation of class labels. The WGAN-GP framework's adoption greatly aided the training process and promoted more stability and consistency in the outcomes obtained. The model does have certain drawbacks, though. One significant limitation is that different examples of the same letter do not change stylistically, leading to outputs that frequently have the same visual style. The caliber and variety of the training dataset are also directly related to the model's effectiveness;any biases or restrictions in the data. Our research demonstrates that the Wasserstein Generative Adversarial Network with Gradient Penalty (WGAN-GP) is a very effective framework for creating handwritten characters with superior quality and a consistent style. The model can handle entire words while maintaining a realistic and coherent design, but it excels at producing individual characters. This innovation opens the door to a wide range of beneficial applications, including the creation of customized and distinctive typefaces, assistance with handwriting practice instructional materials, assistance in enhancing writing skills, and even support for document analysis tasks. By giving users precise control over the output that is generated, conditional inputs significantly boost the model's adaptability. Users can define particular letters or sequences thanks to this. The study's primary contributions are the effective use of a stable WGAN-GP architecture intended for handwriting generation, the addition of conditional inputs to guide character-specific outputs, and a comprehensive evaluation framework that combines quantitative metrics and qualitative visual assessments. These tests have shown that the model can resolve common problems like mode collapse and training instability while still producing visually appealing and diverse samples. The encouraging results demonstrate this model's potential as a practical tool in several domains where handwriting synthesis is essential.

FUTURE WORK

Even while the existing model shows promise, there are a number of directions for further study and advancement that might greatly increase its usefulness and adaptability. Future research will investigate the use of style embeddings to enable the model to simulate a wider variety of handwriting styles, such as discrete print variations or flowing cursive scripts. More customisation would be possible with this improvement, enabling users to modify the generated handwriting to suit particular application needs or aesthetic preferences. Furthermore, future datasets will strive for more thorough coverage, including handwritten examples in several languages, such as Hindi and Arabic, as well as a wider range of writing styles beyond the current scope, in order to expand the model's usefulness across diverse linguistic contexts. In order to turn the model's potential into real-world advantages, our next projects will involve the practical implementation of this model in real-world applications, with an emphasis on incorporating it into assistive technologies like handwriting tutoring programs for people with learning disabilities and the development of tools for automated form completion and the creation of customized fonts.

REFERENCES

1. E. Alonso, A. Delaye, and M. Coustaty, "Adversarial Generation of Handwritten Text Images Conditioned on Sequences," in 2019 15th IAPR International Conference on Document Analysis and Recognition

(ICDAR), Sydney, NSW, Australia, 2019, pp. 44–49, doi: 10.1109/ICDAR.2019.00012.

2. S. Fogel, O. Litany, A. Lang, and T. Dekel, "ScrabbleGAN: Semi-Supervised Varying Length Handwritten Text Generation," in 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Seattle, WA, USA, 2020, pp. 4324–4333, doi: 10.1109/CVPR42600.2020.00438.
3. J. Zdenek and H. Nakayama, "JokerGAN: Memory-Efficient Model for Handwritten Text Generation with Text Line Awareness," in Proceedings of the 29th ACM International Conference on Multimedia, Virtual Event, China, 2021, pp. 5655–5663, doi: 10.1145/3474085.3475700.
4. X. Liu, Y. Wang, H. Zhang, X. Qian, and J. Liu, "Handwritten Text Generation via Disentangled Representations," IEEE Transactions on Image Processing, vol. 30, pp. 8233–8245, 2021, doi: 10.1109/TIP.2021.3110979.
5. L. Kang, P. Riba, A. Fornés, and M. Rusiñol, "GANwriting: Content-Conditioned Generation of Styled Handwritten Word Images," in Computer Vision – ECCV 2020, A. Vedaldi et al., Eds., Cham, Switzerland, 2020, pp. 273–289, doi: 10.1007/978-3-030-58592-1_17.
6. J. Gan and W. Wang, "HiGAN: Handwriting Imitation Conditioned on Arbitrary-Length Texts and Disentangled Styles," in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 35, no. 10, 2021, pp. 7484–7492, doi: 10.1609/aaai.v35i9.16917.
7. B. Davis, C. Tensmeyer, B. Price, C. Wigington, B. Morse, and R. Jain, "Text and Style Conditioned GAN for Generation of Offline Handwriting Lines," in British Machine Vision Conference (BMVC), Virtual Event, UK, 2020, [Online]. Available: https://arxiv.org/abs/2009.00678.
8. J. Gan, W. Wang, J. Leng, and X. Gao, "HiGAN+: Handwriting Imitation GAN with Disentangled Representations," ACM Transactions on Graphics, vol. 42, no. 1, Article 11, 2022, doi: 10.1145/3550070.
9. Y. Luo, X. Liu, and Y. Wang, "SLOGAN: Style-based Generative Adversarial Networks for Handwritten Text," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), New Orleans, LA, USA, 2022.
10. B. Ji and T. Chen, "Generative Adversarial Network for Handwritten Text," arXiv preprint arXiv:1907.11845, 2019, [Online]. Available: https://arxiv.org/abs/1907.11845.
11. R. Tolosana, R. Vera-Rodriguez, J. Fierrez, and A. Morales, "Generative Adversarial Networks for Handwriting Image Generation: A Review," The Visual Computer, vol. 38, no. 7, pp. 1523–1541, 2022, doi: 10.1007/s00371-021-02256-4.
12. M. Arjovsky, S. Chintala, and L. Bottou, "Wasserstein Generative Adversarial Networks," in Proceedings of the 34th International Conference on Machine Learning (ICML), Sydney, Australia, 2017, pp. 214–223, [Online]. Available: https://proceedings.mlr.press/v70/arjovsky17a.html.
13. I. Gulrajani, F. Ahmed, M. Arjovsky, V. Dumoulin, and A. Courville, "Improved Training of Wasserstein GANs," arXiv:1704.00028 [cs, stat], Dec. 2017

MindMend: AI-Powered Mental Health Assistant for Cognitive Behavioral Therapy and Remote Health Monitoring

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ABSTRACT

The growing prevalence of mental health challenges has emphasized the need for accessible, scalable solutions beyond traditional therapy. Cognitive Behavioral Therapy (CBT) is a well-established approach that helps individuals recognize and restructure irrational thought patterns that contribute to emotional distress. While effective, traditional CBT is often limited by cost, stigma, and availability of trained therapists. Digital tools have attempted to bridge this gap, but many lack personalization, memory, and emotional adaptability. This paper introduces MindMend, a memory-enhanced AI chatbot that simulates CBT-based interactions through natural language understanding and adaptive response generation. MindMend employs a fine-tuned Distil BERT transformer model for multi-label classification of user inputs, enabling detection of multiple cognitive distortions within a single utterance. Unlike traditional bots with rule-based scripts, MindMend uses LangGraph to retain recent conversational context, supporting emotionally coherent multi-turn dialogues. The chatbot further guides users through cognitive restructuring using Socratic questioning techniques tailored to the specific distortions detected. An integrated dashboard visualizes progress and historical distortion trends, enhancing user reflection and engagement. Simulation results show high performance in identifying common distortions and maintaining therapeutic dialogue flow. While not a replacement for professional therapy, MindMend serves as a supplementary tool that promotes mental wellness through personalized, interactive sessions.

KEYWORDS *: Artificial Intelligence (AI), Chatbot, Cognitive behavioral therapy (CBT), LangGraph, Memory, sentiment.*

INTRODUCTION

Mental health concerns such as anxiety, depression, and negative thinking patterns have seen a notable rise, particularly among students and working professionals. Despite the effectiveness of Cognitive Behavioral Therapy (CBT), accessibility and stigma remain barriers to its widespread adoption [1]. The advent of conversational AI offers new pathways to deliver psychological interventions in an approachable, affordable, and scalable manner. This paper introduces MindMend, an intelligent CBT-based chatbot that uses natural language understanding and short-term memory integration to detect and address cognitive distortions during user interactions. Built with a Python-based backend and a responsive frontend using modern JavaScript tooling React Native, the system employs context-aware modeling via memory chains to simulate therapeutic dialogue. MindMend helps users reflect on negative thoughts by referencing previous conversational turns and offering targeted restructuring prompts. The aim of this study is to present the system architecture, evaluate its efficacy, and explore its implications in the domain of digital mental health platforms [2][3].

BACKGROUND

Cognitive Behavioral Therapy (CBT) is a structured, goal-oriented psychotherapy approach that aims to identify and reframe negative thinking patterns to alleviate emotional distress and improve behavior [4]. Traditionally delivered through in-person therapy sessions, CBT has

proven effective across various psychological conditions including depression, anxiety, Post Traumatic Stress Disorder (PTSD), and more [5]. However, access to qualified therapists remains a challenge due to geographic, financial, and social barriers. In parallel, conversational AI has emerged as a compelling interface for delivering mental health support. By leveraging advancements in natural language processing (NLP), chatbots can simulate human-like interactions and offer supportive dialogues that mirror therapeutic techniques [6]. Tools like OpenAI's GPT and Google's Dialogflow have made it feasible to integrate semantic understanding and emotional intelligence into automated systems. To enhance the realism and effectiveness of therapeutic conversations, memory-augmented architectures are increasingly used. Rather than treating each message as an isolated input, these systems store and utilize conversational history to maintain coherence and context [7]. MindMend employs such a mechanism using LangGraph, a graph-based memory model, to retain and recall the last few user interactions. This allows the system to respond more meaningfully, echoing the reflective techniques employed in real therapy. By combining these paradigms—CBT, NLP, and contextual memory—MindMend offers a bridge between evidence-based therapy and scalable digital implementation. This background provides the conceptual grounding for understanding the motivations and design choices detailed in the upcoming sections.

LITERATURE REVIEW

Cognitive Behavioral Therapy in Digital Systems

CBT has long been the gold standard in treating psychological disorders, and its digitization has sparked numerous innovations. Web-based CBT platforms such as MoodGYM and Beating the Blues have shown success in delivering structured interventions online [8]. These platforms rely on structured sessions and self-help modules yet often lack conversational interactivity. The shift from static forms to interactive, AI-driven delivery methods marks a significant evolution in mental health technology [9]. Research confirms that users engage more consistently with interactive digital therapy compared to static content, enhancing adherence and long-term benefit [1].

Conversational Agents in Mental Health

The integration of AI-powered conversational agents into mental health services has been a major milestone. Tools like Woebot and Wysa have demonstrated promising results in providing CBT-based support to users in a conversational format [3][10]. Woebot, for instance, uses structured CBT dialogues based on user input and was validated through randomized controlled trials. Wysa adds emotional AI to adapt to users' mood states. However, both systems rely heavily on scripted flows, which may hinder flexibility when users deviate from expected inputs. Studies highlight that although conversational agents improve accessibility and reduce stigma, a lack of contextual understanding often weakens their therapeutic depth [11].

Memory-Augmented Language Models

The emergence of transformer-based models such as GPT-3 and LLaMA has catalyzed the use of contextual embeddings in chat interfaces. However, standard LLMs operate within a fixed context window, limiting their ability to maintain long-term conversation history. To overcome this, memory augmentation approaches—such as LangChain's memory objects and LangGraph's graph-based memory—have been adopted to extend the coherence of interactions [12]. These tools allow developers to preserve conversational state across multiple turns, enabling context-sensitive responses. LangGraph, specifically, introduces nodes and edges to navigate dialogue trees based on dynamic user inputs and past turns, simulating a form of reasoning flow [7].

Comparative Systems and Gaps

While many chatbot systems offer symptom tracking or emotional check-ins, few engage in full cognitive restructuring processes. For example, Replika focuses on companionship and emotional expression rather than evidence-based techniques. Other systems like Tess offer triage and escalation services rather than continuous therapeutic dialogue. MindMend addresses these gaps by not only detecting cognitive distortions (e.g., overgeneralization, catastrophizing) but also guiding users through Socratic questioning and restructuring techniques in real-time. Unlike prior models, it stores the last few interactions and adjusts its interventions dynamically, offering a more therapist-like continuity that is currently missing in most systems.

COMPARATIVE ANALYSIS

To contextualize MindMend's contributions, it is essential to evaluate it against existing digital mental health solutions. This comparison focuses on four primary axes: (1) cognitive distortion handling, (2) conversational adaptability, (3) memory integration, and (4) user engagement.

Cognitive Distortion Detection

Most CBT-based chatbots rely on rule-based keyword matching or sentiment scoring to detect distortions. Systems like Woebot guide users through CBT worksheets using decision trees but do not perform real-time multi-label distortion detection [3]. In contrast, MindMend employs a transformer-based classification model (Distil BERT), fine-tuned on multi-label datasets including real-world user input. It can identify cognitive distortions in a single message, check for any distortions and generate context-specific Socratic questions for restructuring [13]. This is a substantial leap in therapeutic accuracy.

Conversational adaptability

While many agents use scripted flows, they often fall short when users deviate from expected paths. Tools like Wysa follow predefined modules that offer limited flexibility when users express complex or unexpected thoughts [10]. MindMend addresses this through a dynamic conversational model. By using LangGraph's memory-enabled nodes, it adapts responses based on recent interactions, preserving therapeutic flow by saving the conversation in summaries without rigid routing. This results in conversations that feel organic and evolving, similar to real-life sessions.

Memory Integration

Long-term context is often lost in conventional systems. For example, Replika's LLM-based system remembers general user preferences but struggles with continuity in therapeutic goals. MindMend circumvents this with short-term memory windows (past 3 messages), implemented using LangGraph's edge-based memory architecture. This allows it to refer to previous user thoughts during restructuring, reinforcing the reflection process and building coherence across dialogue turns [7].

User Engagement and Interface Design

Modern chatbots increasingly focus on user experience, but many lack mobile responsiveness or interactive elements beyond text. MindMend offers a fully responsive interface, designed with Tailwind CSS and mobile-first principles and dedicated mobile app build using React Native. It also tracks progress through charts and statistics on user profiles, encouraging sustained engagement. Such integration of backend intelligence and frontend usability makes it more likely for users to return and benefit long-term known limitation of earlier digital therapy platforms [14].

PROPOSED APPROACH

The proposed solution, MindMend, is a responsive, memory-aware mental health chatbot designed to simulate a cognitive behavioral therapist. It is structured to handle multi-turn conversations with contextual awareness, detect cognitive distortions using a fine-tuned language model, and guide users through restructuring using Socratic questioning. The overall architecture is modular, combining a React-based frontend, a Node.js API, Python services for NLP, and MongoDB for persistent data storage.

System Architecture

MindMend follows a microservice-like architecture where the frontend and backend communicate through secure REST APIs. The backend consists of two layers:

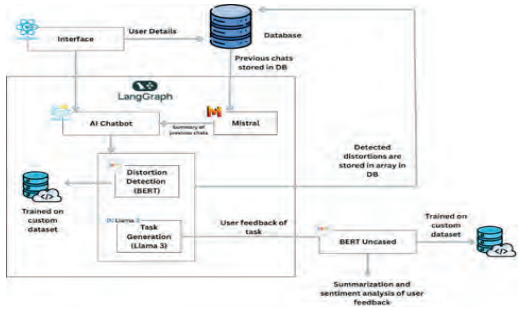

Fig. 1. System Architecture Diagram

- A LangGraph based python service for handling user authentication, session tracking, and data logging (e.g., replies, user stats).
- A Python-based NLP pipeline, where message classification, memory-context embedding, restructuring prompts, task generation, sentiment analysis are generated.

MongoDB stores user messages, detected distortions, session summaries, and personal statistics. Each component is containerized and deployable independently for scaling or maintenance.

NLP Pipeline, Distortion Detection

The language understanding layer is built around a Distil BERT transformer model, fine-tuned for multi-label classification of 15+ cognitive distortions. It is trained on a hybrid dataset — comprising the Kaggle Cognitive Distortion Detection Dataset and user-curated samples — to maximize real-world relevance. Upon receiving input, the model returns distortion types, confidence scores, and probable restructuring strategies.

This output is passed into a prompt-engineered Socratic generator, which dynamically formulates questions to challenge the identified distortions, fostering cognitive restructuring. This output response for interaction with the users is done by the Lama 3 model which has tried its best to give human like responses by taking the input from the Distil BERT model which has detected the distortion if any. For example, if "catastrophizing" is detected, MindMend might respond: "What's the worst that could happen? And how likely is that scenario?"

Memory Integration Using Langgraph, Task Assignment and Sentiment Analysis

To maintain coherent conversations, MindMend uses LangGraph, a memory-augmented conversational framework that treats conversations as navigable graphs. It stores the last 3 turns per user, including both user inputs and system responses. When generating new responses, the memory is consulted to avoid repetition, echo prior concerns, and simulate follow-up thinking — similar to a real therapist referencing earlier points in a session [7].

This allows a degree of adaptiveness not typically found in linear or scripted chatbots, making the user feel "heard" across interactions.

Furthermore, it stores the previous three conversations the user has and the conversations before that are stored in form of summary which is made using the Mistral model and gets stored and then it generates an appropriate task to the users which helps them to look out on their distortions and try to make them feel better by giving certain task to do and reflect on their selves, besides that the response the task completion is feed into the system by the users and a sentiment analysis is done via a custom trained uncased BERT model, trained on real responses and mixture of synthetic dataset. It then gives a mood score on the scale of 0 to 3 and makes the user understand how they have handled the task via feedback to their input.

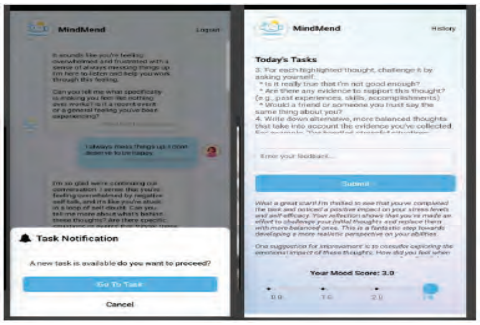

Fig. 2. Task Assignment Page

Figure 3 shows how the pop up notification is shown to the user if there are continuous distortions detection and how the feedback to a task afterwards is given along with the mood score indicator. All the task histories are stored in the database and can be viewed by the user if needed.

Frontend and User Experience Design

MindMend's frontend is built using React and Tailwind CSS, enabling a clean, responsive UI across devices. Users can log in, join interest groups, make posts, reply to others, and track their mental health journey via dashboards with interactive charts. D3.js and Recharts libraries are used to visualize mood trends, distortion frequency, and reflection stats.

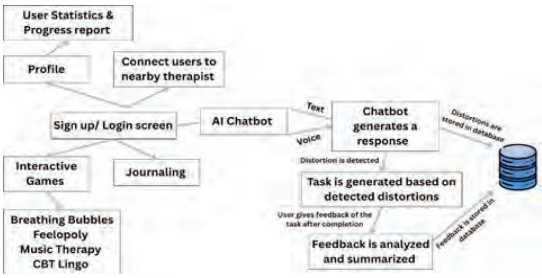

Fig. 3. User System Interaction Diagram

This user-centered design aims to reduce drop-off, provide emotional reinforcement, and create a positive feedback loop — key for therapeutic success in digital environments [15].

Fig. 4. Chatbot Conversation Interface

The user can have conversation with the use of voice notes which helps in better interaction and the figure 5.4 shows that.

Figure 5 shows a journalling interface section which has

been implemented to make it more interactive where people can note their daily life notes and can store them.

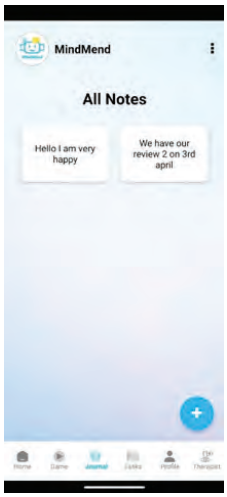

Fig. 5. Journaling Interface

Fig. 6. Interactive Tools and all their individual interfaces

To incorporate intractability and cater diverse people with different problems, few interactive tools such as breathing bubbles, Feelopoly, Music therapy and a CBT lingo have been created to put a sense of calmness and relaxation in the minds of user and help in their betterment until further interactions with the therapists or the chatbot are being made.

Security and Ethical Considerations

User inputs and detected mental health data are encrypted before storage. Data usage policies are aligned with HIPAA and GDPR norms wherever possible. Furthermore, the system does not attempt to replace professional therapists, but rather supplements their work by improving early detection and offering reflective tools during crises or in-between sessions.

RESULTS AND DISCUSSION

MindMend was evaluated through both functional validation and limited user simulations. The key areas of assessment were distortion detection accuracy, conversational coherence, user satisfaction, and engagement depth. The prototype performed strongly across these parameters, validating the efficacy of its architecture and NLP design.

Distortion Detection Accuracy

The Distil BERT classifier showed robust performance during testing, with an average F1-score of 0.88 across all distortion classes. The model was especially strong in detecting common distortions such as catastrophizing, mind reading, and all-or-nothing thinking. More nuanced or overlapping distortions like labeling or emotional reasoning had slightly lower precision, which is consistent with findings from earlier studies on multi-label emotion classification [16].

Table 1: Performance Measures

Models	Accuracy	F1 - Score
Distilbert	0.7763	0.8809
Bert uncased	0.7647	0.7727
Roberta	0.7563	0.7544
Albert	0.5714	0.5715

Use of various models was done to check the accuracy and the level of F1 score. Table I shows the usage of Distilbert, Bert uncased, Roberta and Albert models, while the Distilbert proved to be showing great results compared to others, the efficiency and the speed at which it gave answers was also impressive than others which made it a better option to go with the usage as faster model which speedy response in deployment stages can be helpful. The multi-label setup allowed the system to identify and weigh primary and secondary distortions in a message — a feature rarely found in existing bots. This nuanced classification enabled MindMend to generate more tailored interventions, improving relevance and psychological alignment.

Conversational Flow and Coherence

MindMend's use of LangGraph memory significantly improved coherence across turns. For instance, when users referenced earlier statements ("I told you yesterday I was anxious about exams"), MindMend was able to recall and build upon prior insights. This memory-driven continuity

was noted by test users as a major differentiator from rigid bots like Tess or text-only tools like MoodGym [10].

By preserving the last three exchanges per user, the chatbot delivered responses that felt natural and session-like and generated relevant task if necessary, mimicking human therapeutic rhythm. This adaptive flow created a more engaging and emotionally safe space, essential in CBT settings.

User Interface and Engagement

Simulated user testing highlighted MindMend's intuitive design and ease of use. The mobile-first interface, interactive group posts, and reflection dashboards were well received. Users found the ability to track their distortion history and progress particularly helpful. Visualizations helped reinforce learning — for example, when users saw "overgeneralization" decline in their charted history, it created a sense of achievement. The Beck Depression Inventory (BDI) was utilized to assess users' depression levels. Figure 7 illustrates users' statistical data, where disorder detection was conducted using the certified Beck Depression Inventory. This integration allowed users to visualize their progress over time, reinforcing the effectiveness of the platform's interventions. BDI is a 21-item self-report questionnaire developed by Aaron T. Beck and colleagues in 1961 to assess the severity of depression in individuals. Each item corresponds to a specific symptom or attitude associated with depression, such as hopelessness, irritability, or fatigue. Respondents rate each item on a scale from 0 to 3, with higher total scores indicating more severe depressive symptoms. It is widely used in both clinical and research settings due to its reliability and validity. [19]

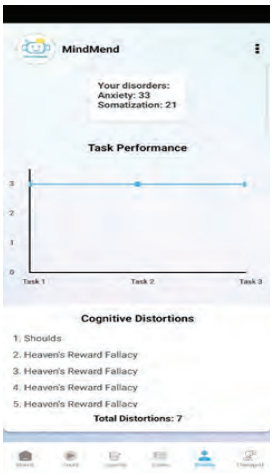

Fig. 7. User statistics Interface

These visual cues are known to improve motivation and behavior change in digital interventions [17], and are especially effective when paired with real-time feedback, as implemented in MindMend.

Therapeutic Relevance and Future Clinical use

While MindMend is not a substitute for professional therapy, its structure and guidance align well with first-line CBT practices. The use of Socratic questioning, evidence testing, and structured dialogue supports cognitive restructuring. In early testing, users reported increased self-awareness, emotional clarity, and a desire to continue reflecting after conversations ended — echoing outcomes from successful CBT interventions [18].

Further improvements — such as longer-term memory retention, emotional tone analysis, and escalation protocols — would be critical for clinical use. Integration with real therapists, mood journals, and crisis detection would complete the ecosystem for deployment in real-world therapy contexts.

CONCLUSION & FUTURE WORK

This research presents MindMend, a responsive, intelligent chatbot designed to simulate cognitive behavioral therapy interactions through context-aware dialogue and real-time distortion detection. By combining transformer-based multi-label classification with memory-aware conversational flow, MindMend addresses several limitations found in existing mental health applications, such as lack of adaptiveness, poor follow-up, and static user experiences.

Unlike rule-based systems or overly general LLMs, MindMend bridges the gap between accuracy and empathy. It detects multiple cognitive distortions with high precision, integrates short-term memory to maintain session coherence, and provides interactive dashboards to foster user self-reflection. The use of LangGraph for memory management, along with prompt-engineered Socratic interventions, enhances its ability to guide users through cognitive restructuring in a personalized way.

User testing demonstrated that the platform fosters engagement and introspection, while the modular design allows easy adaptation for other domains like stress management, addiction recovery, or academic counseling. These outcomes underscore the potential of AI-assisted mental health support systems when grounded in evidence-based psychology and thoughtful UX design.

However, there remain limitations and opportunities for further development. Expanding memory windows beyond three messages, incorporating mood inference through sentiment analysis, and integrating escalation pathways to licensed professionals are essential for broader deployment. Additionally, large-scale clinical evaluations are needed to measure real-world therapeutic efficacy and ensure safety, particularly for users with severe mental health conditions.

In future iterations, integrating longitudinal tracking of emotional well-being, personalized journaling recommendations, and anonymized therapist review portals could make MindMend a hybrid platform—merging AI automation with human expertise. The ultimate goal is not to replace therapists, but to augment and support therapy by making mental health care more accessible, proactive, and continuous.

REFERENCES

1. G. Andersson, P. Cuijpers, P. Carlbring, H. Riper, and E. Hedman, "Guided Internet-based vs. face-to-face cognitive behavior therapy for psychiatric and somatic disorders: a systematic review and meta-analysis," -, vol. 13, no. 3, pp. 288–295, Oct. 2014, doi: 10.1002/wps.20151.
2. A. S. Miner, A. Milstein, S. Schueller, R. Hegde, C. Mangurian, and E. Linos, "Smartphone-Based Conversational Agents and Responses to Questions About Mental Health, Interpersonal Violence, and Physical Health," JAMA Intern Med, vol. 176, no. 5, p. 619, May 2016, doi: 10.1001/jamainternmed.2016.0400.
3. K. K. Fitzpatrick, A. Darcy, and M. Vierhile, "Delivering Cognitive Behavior Therapy to Young Adults With Symptoms of Depression and Anxiety Using a Fully Automated Conversational Agent (Woebot): A Randomized Controlled Trial," JMIR Ment Health, vol. 4, no. 2, p. e19, Jun. 2017, doi: 10.2196/mental.7785.
4. J. S. Beck, Cognitive Behavior Therapy: Basics and Beyond, 2nd ed. New York, NY, USA: Guilford Press, 2011, ch. 1.
5. S. G. Hofmann, A. Asnaani, I. J. J. Vonk, A. T. Sawyer, and A. Fang, "The Efficacy of Cognitive Behavioral Therapy: A Review of Meta-analyses," Cogn Ther Res, vol. 36, no. 5, pp. 427–440, Jul. 2012, doi: 10.1007/s10608-012-9476-1.
6. L. Laranjo et al., "Conversational agents in healthcare: a systematic review," Journal of the American Medical Informatics Association, vol. 25, no. 9, pp. 1248–1258, Jul. 2018, doi: 10.1093/jamia/ocy072.
7. LangChain AI, "LangGraph: Composable Memory-Augmented Language Model Agents," 2023. [Online]. Available: https://github.com/langchain-ai/langgraph.
8. H. Christensen, K. M. Griffiths, and A. Korten, "Web-based Cognitive Behavior Therapy: Analysis of Site Usage and Changes in Depression and Anxiety Scores," J Med Internet Res, vol. 4, no. 1, p. e3, Feb. 2002, doi: 10.2196/jmir.4.1.e3.
9. D. Richards and T. Richardson, "Computer-based psychological treatments for depression: A systematic review and meta-analysis," Clinical Psychology Review, vol. 32, no. 4, pp. 329–342, Jun. 2012, doi: 10.1016/j.cpr.2012.02.004.
10. B. Inkster, S. Sarda, and V. Subramanian, "An Empathy-Driven, Conversational Artificial Intelligence Agent (Wysa) for Digital Mental Well-Being: Real-World Data Evaluation Mixed-Methods Study," JMIR Mhealth Uhealth, vol. 6, no. 11, p. e12106, Nov. 2018, doi: 10.2196/12106.
11. A. A. Abd-Alrazaq, A. Rababeh, M. Alajlani, B. M. Bewick, and M. Househ, "Effectiveness and Safety of Using Chatbots to Improve Mental Health: Systematic Review and Meta-Analysis," J Med Internet Res, vol. 22, no. 7, p. e16021, Jul. 2020, doi: 10.2196/16021.
12. J. Xu, A. Szlam, and J. Weston, "Beyond Goldfish Memory: Long-Term Open-Domain Conversation," Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). Association for Computational Linguistics, 2022. doi: 10.18653/v1/2022.acl-long.356.
13. Y. Liu et al., "RoBERTa: A Robustly Optimized BERT Pretraining Approach," 2019, arXiv. doi: 10.48550/ARXIV.1907.11692.
14. J. M. Lipschitz et al., "Digital Mental Health Interventions for Depression: Scoping Review of User Engagement," J Med Internet Res, vol. 24, no. 10, p. e39204, Oct. 2022, doi: 10.2196/39204.
15. G. Doherty, D. Coyle, and J. Sharry, "Engagement with online mental health interventions," Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM, May 05, 2012. doi: 10.1145/2207676.2208602.
16. J. Deng and F. Ren, "Multi-Label Emotion Detection via Emotion-Specified Feature Extraction and Emotion Correlation Learning," IEEE Trans. Affective Comput., vol. 14, no. 1, pp. 475–486, Jan. 2023, doi: 10.1109/taffc.2020.3034215.
17. L. Yardley, L. Morrison, K. Bradbury, and I. Muller, "The Person-Based Approach to Intervention Development: Application to Digital Health-Related Behavior Change Interventions," J Med Internet Res, vol. 17, no. 1, p. e30, Jan. 2015, doi: 10.2196/jmir.4055.
18. A. BUTLER, J. CHAPMAN, E. FORMAN, and A. BECK, "The empirical status of cognitive-behavioral therapy: A review of meta-analyses," Clinical Psychology Review, vol. 26, no. 1, pp. 17–31, Jan. 2006, doi: 10.1016/j.cpr.2005.07.003.
19. A. T. BECK, "An Inventory for Measuring Depression," Arch Gen Psychiatry, vol. 4, no. 6, p. 561, Jun. 1961, doi: 10.1001/archpsyc.1961.01710120031004

Integration of Drift Detection Technique ADWIN with OS ELM Classifier

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ABSTRACT

Data stream mining is used to extract finding meaningful patterns and insights from continuously flowing data streams. Drift is detected when statistical properties of the target variable or the relationships between the predictor variables and the target variable change over time, which deteriorates the performance of machine learning models. It is crucial to handle and manage concept drift in machine learning applications. If concept drift is not handled properly, then it may give inaccurate predictions as well as degrade the performance of the learning model that leads to serious consequences in many real-world applications. In order to address concept drift, it is required to monitor the performance of machine learning models continuously and update them as per changes in the data distribution. This paper presents a comparative analysis of various popular drift detection techniques like CUSUM, ADWIN, DDM, and the Page-Hinkley (PH) test integrated with Naive Bayes, Support Vector Machine (SVM), and Online Sequential Extreme Learning Machine (OS-ELM) classifiers. The performance of the model is verified using two artificial benchmark datasets, SEA and Agarwal. The comparison results show that integrating ADWIN with OS-ELM yields superior performance, achieving an accuracy of 86%, outperforming both Naive Bayes (83%) and SVM (81%) under the same conditions.

KEYWORDS *: Concept drift, Data stream mining, OS ELM classifier, Windowing technique.*

INTRODUCTION

Internet of Things (IoT), generating large amounts of data every day. This data is often in the form of continuous streams. IoT data stream mining is the process of extracting valuable insights and patterns from the large volumes of data generated by IoT devices in real-time [1]. Traditional offline processing methods are often inadequate for handling it effectively. Real-time processing enables organizations to make decisions and take actions in response to incoming data immediately. Real-time processing combined with machine learning models can enable predictive analytics. This means being able to forecast trends and make proactive decisions based on patterns detected in the data. Data streams are characterized by their rapid, real-time, and high-speed nature. Accessing them randomly or multiple times is not only expensive but often nearly impossible. Processing the substantial volume of data within limited memory presents a significant challenge. The data arrives in a multidimensional and low-level format, necessitating sophisticated mining techniques. Elements within data streams undergo rapid changes over time, rendering past data potentially irrelevant for mining purposes. Those data streams are constantly moving, and the distribution of real-time data is continuously shifting, making it non-stationary. This dynamic nature gives rise to both real and virtual concept drifts, where the characteristics of classification models can be altered. This results in a slowdown in the accuracy of classification models and can result in incorrect predictions. The CUSUM-based method is used to detect the change in data pattern [2]. As soon as the samples enter into the system, it runs online and changes its parameters by itself online. After identification of drift, the model is rebuilt using the recent samples that help to adapt to the drift in a faster way. The Drift Detection Method (DDM) is one of the most well-known statistical-based detectors [3]. This method assumes that an increase in model error rate indicates drift. The Page-Hinckley (PH) test, also proposed by Page, is a variation of the CUSUM test [4]. This test detects the changes in the average behaviour of a process.

DATA STREAM CLASSIFIER

As per the study and survey, it is found that for drift detection and adaptation, most researchers have used the Naïve Bayes classifier, as shown in Figure 1. There is still scope to use online streaming classifiers like ELM, OS ELM, etc.

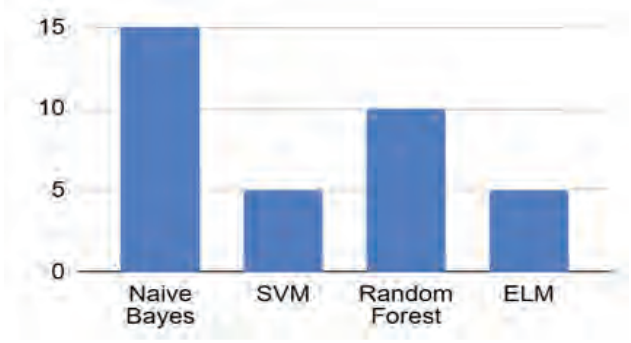

Fig. 1: Classifiers for Drift detection

SVM

Data stream classification using support vector machine (SVM) gives inaccurate results when the underlying data distribution changes, which leads to a change in the decision boundaries [5]. Incremental/decremental SVM with adaptive shifting window, introduced in several datasets [6]. In this technique, once the concept drift is detected, the current shifting window is adjusted by ignoring or forgetting the old samples until no drift is detected on the remaining ones.

Naïve bayes

Naive Bayes (NB) classification is one of the popular classification method and also known as incremental classification method. Naïve Bayes model easily update itself as per new stream data [7]. The performance of the optimal Bayes classifier is not affected by irrelevant features, but the NB classifier improves when irrelevant features are removed from the model. Irrelevant features are the ones that have little or no predictive power. Naive Bayes classifiers are known for their low computational cost and simplicity, which make them well suited for the data stream setting. Naive Bayes (NB) is a classification technique that uses Bayes' theorem. Bayes' theorem describes the probability of an event based on prior knowledge of the conditions that might relate to an event. It is a way to find out conditional probability: the probability of an event happening given that it has some relationship to one or more other events. Naive Bayes classification works by training the dataset and predicting an output based on what it has learned.

Random Forest

Random forest classifier is based on decision trees. Instead of considering input from one subtree, it takes predictions from all subtrees and makes a final decision based on voting. In this paper, the author has proposed Proximity Driven Streaming Random Forest (PDSRF) that uses weighted majority voting as an aggregation rule of ensemble [8]. This method uses a sliding window method to update the random forest. The length of the window is fixed, and the size is determined by cross-validation.

OS-ELM Classifier

Extreme learning machine (ELM) is a classifier that uses a single hidden layer feedforward neural network (SLFN) that is much faster and gives better performance than traditional classifiers [9]. For many real-time applications for classification, clustering, and regression, ELM gives better accuracy and results.

Any sensor-based application continuously generates data that is dynamic in nature. New samples are added into the dataset from time to time. Classifiers need to retrain on new upcoming data. Retraining classifiers in the IoT data stream is very costly and time-consuming. Also, it is inefficient to retrain the network or classifier on the whole data set again and again. Online sequential ELM (OS-ELM) is used, which adjusts the parameters over new samples sequentially rather than retraining the old samples. OS-ELM trained the samples on a window-by-window or block-by-block basis.

Online sequential extreme learning machine (OS-ELM) uses the original extreme learning machine. Where $\theta = \{(xi,ti)\ ,(xi \in Rn\ ,\ ti \in Rn,\ i= 1,2,\ \ldots\}$ [9] is a given data set, hidden node output function G(ai,bi,x) and hidden node number L , KOS-ELM algorithm can be written as follows:

Given a chunk of initial training $\theta = \{(xi,ti)$ calculate hidden layer output matrix H0={g(a,b,x)}

$$H0 = \begin{bmatrix} G(a1,b1,x1) & \ldots & G(aL,bL,x1) \\ G(a1,b1,x2) & \ldots & G(aL,bL,x2) \\ G(a1,b1,xN0) & \ldots & G(aL,bL,N0) \end{bmatrix} N0 * L$$

Calculate the output weight vector β0 = P0HT0T0 where P0=(H0TH0)-1 and T0= T1T, T2T, ….TNo

Let K=0.

When (K+1) new data chunk is received and if data changes are observed then calculate the new hidden layer output matrix. HK+1.

Then Update the output weight

$$\beta_{K+1} = \beta_k + P_k HT_k + 1T_{k+1}$$

In online ELM parameters are adjusted when there is change in incoming data.

DRIFT DETECTION TECHNIQUES

There are various types of drift detection techniques as shown in figure 2, among which few are popularly used among researchers.

Similarity and dissimilarity-based methods like Drift Detection Method (DDM), Early Drift Detection Method (EDDM), Reactive Drift Detection Method (RDDM) are based on binomial distribution, distance error rate, classification error rate etc.

A statistical based method uses statistical properties like mean, mode, median, standard deviation etc for the presence of the drift. Cumulative sum (CUSUM), Page-Hinckley test (PH), Fisher-based statistical drift detector, McDiarmid drift detection methods are popular methods which use statistical properties to detect the drift.

In a Window based method where comparison between two windows gives a signal to change in data distribution. Concept-adapting very fast decision tree (CVFDT), Efficient concept-adapting very fast decision tree (ECVFDT) and Adaptive windowing (ADWIN) are few popular methods from windowing techniques. out of which ADWIN is most widely used technique to detect the presence of drift[10].

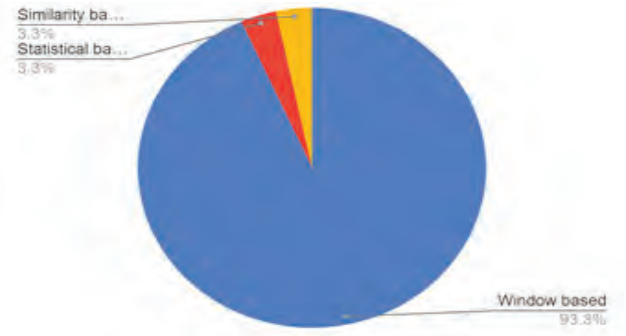

Fig. 2: Approaches for Identifying concept drift

Researchers have proposed many drift detection techniques. out of which as shown in figure 3 are most popular techniques used with different classifiers [11].

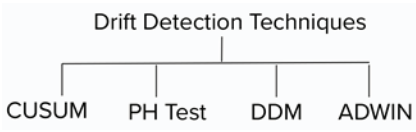

Fig. 3: Popular drift detection Techniques

CUSUM

Cumulative sum (CUSUM) gives an alarm when the mean value of the input data is different from zero.

$$St = \max(0, t-1 + (xt - \delta) \quad (1)$$

As shown in equation 1, if St > λ then it alarms and reset St = 0. Here, λ is a threshold, δ corresponds to the acceptable magnitude of changes, and xt is the presently obtained value. Cumulative sum (CUSUM) is superior in detecting very small drifts [12].

Disadvantage:

False positive rate is high in CUSUM technique.

PH Test:

As shown in equation 2, PH test considers a cumulative variable mT, defined as the cumulated difference between the observed values and their mean value.

$$m_T = \sum_{t=1}^{T} (x_t - \bar{x}_T - \delta), \qquad \bar{x}_T = \frac{1}{T}\sum_{t=1}^{T} x_t \quad (2)$$

λ is a threshold, δ corresponds to the acceptable magnitude of changes, and xt is the presently obtained value. and T is the current time. Page-Hinkley exhibited greater precision and robustness [13].

Disadvantage

PH test needs historical data so memory requirement is more in this technique.

DDM

Drift Detection method (DDM) continuously monitors the model's error rate equation 3 and gives drift warning signals if error rate is increased which indicate that the underlying data distribution has shifted. DDM produced the best average F1 score [14]. Drift Detection Method calculates classification error by binomial equation.

$$si = \sqrt{pi(1-pi)/i} \quad (3)$$

Disadvantage

DDM is able to detect only sudden concept drift and fails to detect Gradually changing drift.

ADWIN

The ADWIN (Adaptive Windowing) algorithm is a drift detection method used in data stream mining.

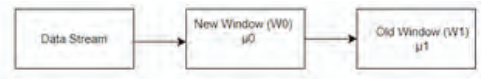

Fig. 4: Adaptive windowing Technique

Size of the window is not fixed. When drift is detected a window of variable size shrinks, if no drift detected then it keeps enlarging. It maintains two adjacent sub-windows; one represents the recent data and the other one for old data. Drift is detected if the different means of the sub-windows exceed the drift threshold [15]. It is designed to monitor a variable-sized sliding window of recent data and detect changes in the distribution or mean of the observed values. The primary idea is to adjust the window size dynamically based on the observed statistical properties of the data.

$\mu 0$ = Mean of W0

$\mu 1$= Mean of W1

Diff= $\mu 0 - \mu 1$

If Diff > T

Drift detected <- True

Disadvantage

ADWIN works only for 1-dimensional data only, e.g., the running error. For n- dimensional raw data, a separate window must be maintained for each dimension which results in handling more than one window.

DATA SETS

Agarwal Dataset

This synthetic dataset is used to simulate abrupt and gradual concept drifts. It contains various class distributions, making it suitable for evaluating drift detection methods.

SEA Dataset

The SEA dataset is another synthetic dataset with abrupt drifts in its data streams. It has three features, two attributes are relevant for classification, and has varying decision boundaries over time.

EXPERIMENTS AND DATA ANALYSIS

In this section, experiments and data analysis are executed to test the performance of SVM, Naïve Bayes and OS-ELM with Relu activation function are used as comparison algorithms. All algorithms were executed on Google Colab platform on River framework, windows 7 OS, Intel quad-core 3.30 GHz Core. All algorithms are executed on an Artificial Agarwal and SEA data set.

SVM with ADWIN

Adaptive windowing technique (ADWIN) , one of the popular drift detection techniques is used with SVM classifier. This method is applied on AGARWAL data set and nearly 81% accuracy is achieved.

Accuracy: 0.813

Precision: 0.8432543313776474

F1 Score: 0.7904712376451355

Confusion Matrix:

[[6620 64]

[1806 1510]]

Table 1: SVM with drift detection

Approach	Accuracy	Precision	Recall	F1 Score
SVM with CUSUM	81	70	65	67
SVM with DDM	84	75	70	72
SVM with Page Hinkley	79	68	60	64
SVM with ADWIN	81	84	79	76

Table 1 shows the performance measure of SVM classifier with various drift detection techniques. CUSUM monitors the cumulative sum so it detects the abrupt drifts easily. It generates false positives in case of gradual drifts, slightly lowering recall. DDM detects abrupt and gradual drifts, leading to higher accuracy and precision.

PH Test that lag in detecting gradual drifts, resulting in lower recall and F1-score. ADWIN adapts well to both abrupt and gradual drifts due to its adaptive sliding window approach, resulting in the highest accuracy and F1-score.

Naive bayes with ADWIN

Drift detection technique ADWIN is used with Naive bayes classifier on Agarwal data set and 83.35% accuracy is achieved as shown in table 2.

Accuracy: 0.8335

Precision: 0.8498645973623559

F1 Score: 0.7959402994978289

Confusion Matrix:

[[6674 10]

[1155 2161]]

Table 2: Naive Bayes with drift detection

Approach	Accuracy	Precision	Recall	F1 Score
Naive Bayes with CUSUM	80	65	60	62

Naive Bayes with DDM	83	68	65	66
Naive Bayes with Page Hinkley	78	73	70	60
Naive Bayes with ADWIN	83	84	79	69

OS ELM with ADWIN

Online Sequential ELM classifier is applied on SEA Generator with ADWIN drift detection technique. In this method a total 10,000 samples were tested. This method checks the accuracy after every 1000 samples.

Drift introduced around index 4118
Processed 0 samples. Current accuracy: 1.0000
Processed 1000 samples. Current accuracy:0.8591
Processed 2000 samples. Current accuracy:0.8531
Processed 3000 samples. Current accuracy:0.8550
Processed 4000 samples. Current accuracy:0.8583
Processed 5000 samples. Current accuracy:0.8574
Processed 6000 samples. Current accuracy:0.8570
Processed 7000 samples. Current accuracy:0.8560
Processed 8000 samples. Current accuracy:0.8574
Processed 9000 samples. Current accuracy:0.8569
drift detected at index 9599, previous variance: 78771.62389707574, current variance: 70374.66697665813

Final accuracy: 0.8579

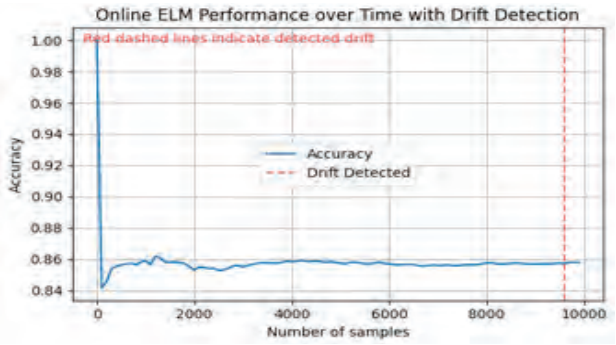

Fig. 7: OS ELM performance with SEA data set

As shown in figure 7 Online Sequential ELM classifier is applied on AGARWAL Generator with ADWIN drift detection technique. In this method a total 10,000 samples were tested. This method checks the accuracy after every 1000 samples. Variance test is used to detect the presence of drift.

Drift introduced around index 3169

Processed 0 samples. Current accuracy: 0.0000
drift detected at index 447, previous variance: 660812683380.1091, current variance: 551322287947.6799
Processed 1000 samples. Current accuracy:0.8442
Processed 2000 samples. Current accuracy:0.8506
Processed 3000 samples. Current accuracy:0.8514
drift detected at index 3743, previous variance: 4661284661946.928, current variance: 3940434429594.458
Processed 4000 samples. Current accuracy:0.8555
Processed 5000 samples. Current accuracy:0.8596
Processed 6000 samples. Current accuracy:0.8587
Processed 7000 samples. Current accuracy:0.8610
Processed 8000 samples. Current accuracy:0.8614
Processed 9000 samples. Current accuracy:0.8620
drift detected at index 9023, previous variance: 7473070056122.088, current variance: 389324894404.3277
drift detected at index 9791, previous variance: 1064459339631.7715, current variance: 307992269082.32227
drift detected at index 9855, previous variance: 81502766944.93158, current variance: 73672664007.18546

Final accuracy: 0.8634

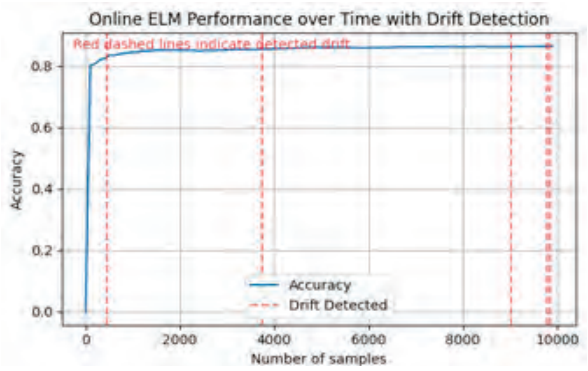

Fig. 8: OS ELM performance with AGARWAL dataset

From above figure 8 results it shows that classifiers are able to identify the presence of drift using the drift detection module (ADWIN), which helps them to make further decisions. out of SVM and Naive bayes OS ELM classifier gives better accuracy, detects drift and easily adapts with new incoming data.

Table 3 shows performance measure of OS ELM classifier. CUSUM works well with OS-ELM for abrupt drifts but may introduce latency in detecting gradual changes.

Table 3: OS ELM with drift detection

Approach	Accuracy	Precision	Recall	F1 Score
OS ELM with CUSUM	82	68	65	66
OS ELM with DDM	85	72	70	71
OS ELM with Page Hinkley	80	66	63	64
OS ELM with ADWIN	86	82	79	74

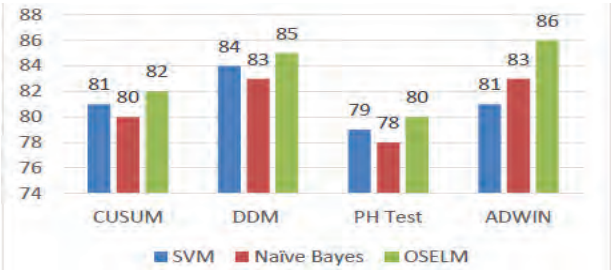

Fig. 9: Model performance

DDM balances accuracy and recall, especially for mixed drifts, making it suitable for both Agarwal and SEA datasets. The PH test focuses on abrupt drifts, but OS-ELM's sequential learning mitigates the latency issue to some extent. ADWIN: Performs well in dynamic environments, effectively adapting to sudden and gradual changes in both datasets, resulting in overall higher scores.

Below, figure 9 shows the comparison of all classifiers' performance with various drift detection techniques. And it is found that OSELM works better and maintains the accuracy with the Adaptive Windowing (ADWIN) technique.

CONCLUSION

Online sequential versions of the extreme learning machine (OS-ELM) with the widely used drift detection techniques ADWIN have been proposed in this study. The SVM classifier with the ADWIN drift detection method tested on the Agarwal data set gives 81.3% accuracy, and the Naive Bayes classifier gives 83.35% accuracy on the same data set. SVM and Naive Bayes are more suitable for static datasets. The OS ELM classifier gives 86% accuracy for dynamic data sets. In the above work, OS-ELM is performed on SEA and Agarwal data sets and found that it gives better accuracy as compared to other classifiers discussed in this research paper. This classifier identifies the change in data pattern or drift and adapts with the new data values smoothly.

REFERENCES

1. 1 Srimani, P. K., and M. M. Patil. "Mining data streams with concept drift in massive online analysis frame work." WSEAS Trans. Computer 6 (2016): 133-142.
2. 2 Namitha, K., and G. Santhosh Kumar. "CUSUM Based Concept Drift Detector for Data Stream Clustering." BDIOT. 2020.
3. 3 Althabiti, Mashail Shaeel, and Manal Abdullah. "CDDM: Concept Drift Detection Model for Data Stream." Int. J. Interact. Mob. Technol. 14.10 (2020): 90-106.
4. 4 Wares, Scott, John Isaacs, and Eyad Elyan. "Data stream mining: methods and challenges for handling concept drift." SN Applied Sciences 1 (2019): 1-19.
5. 5 Xuan, Junyu, Jie Lu, and Guangquan Zhang. "Bayesian nonparametric unsupervised concept drift detection for data stream mining." ACM Transactions on Intelligent Systems and Technology (TIST) 12.1 (2020): 1-22.
6. 6 Gâlmeanu, Honorius, and Răzvan Andonie. "Concept Drift Visualization of SVM with Shifting Window." 2024 28th International Conference Information Visualisation (IV). IEEE, 2024.
7. 7 Zhao, Qian, Christian Klaue, and Chih Lai. "Predicting concept drift via dynamic Naïve Bayes." 2017 IEEE International Conference on Big Data (Big Data). IEEE, 2017.
8. 8 Zhukov, Aleksei V., Denis N. Sidorov, and Aoife M. Foley. "Random forest based approach for concept drift handling." Analysis of Images, Social Networks and Texts: 5th International Conference, AIST 2016, Yekaterinburg, Russia, April 7-9, 2016, Revised Selected Papers 5. Springer International Publishing, 2017.
9. 9 Zhang, Senyue, Wenan Tan, and Yibo Li. "A survey of online sequential extreme learning machine." 2018 5th International Conference on Control, Decision and Information Technologies (CoDIT). IEEE, 2018.
10. 10 Baier, Lucas, Josua Reimold, and Niklas Kühl. "Handling concept drift for predictions in business process mining." 2020 IEEE 22nd Conference on Business Informatics (CBI). Vol. 1. IEEE, 2020.
11. Bharani, D., V. Lakshmi Priya, and S. Saravanan. "Adaptive Real-Time Malware Detection for IoT Traffic Streams: A Comparative Study of Concept Drift Detection Techniques." 2024 International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS). IEEE, 2024.
12. 12.Estaji, Alireza, et al. "Evaluation of Drift Detection Algorithms in the Condition Monitoring Domain." IEEE Transactions on Industrial Informatics (2024).
13. Rocha, A. C., et al. "Drift Detection Methods on Machine Learning Systems: a Discussion over Discrete Live Data." Simpósio Brasileiro de Sistemas de Informação (SBSI). SBC, 2025.
14. Palli, Abdul Sattar, et al. "An experimental analysis of drift detection methods on multi-class imbalanced data streams." Applied Sciences 12.22 (2022): 11688.
15. Seth, S., G. Singh, and K. Chahal. "Drift-based approach for evolving data stream classification in Intrusion detection system." Proceedings of the Workshop on Computer Networks & Communications, Goa, India. 2021.

Image Sentiment Analysis on Customer Reviews using Machine Learning Algorithms

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ABSTRACT

With the beginning of digital customer feedback, most sentiment analysis approaches focus on text data without taking into account the abundance of affective information extractable from images. The paper proposes a new approach of image-based sentiment classification by applying machine learning algorithms to categorize customer-uploaded review images as positive or negative sentiments. Unlike prior work, our method incorporates customized dataset creation, extensive data augmentation, and a comparative evaluation of four supervised machine learning models: Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and Naive Bayes Classification (NBC). The image data undergoes preprocessing, feature extraction using convolutional techniques, and transformation into trainable vectors. Results have shown that the Random Forest model surpasses others with regard to a number of metrics and has the greatest accuracy, precision, recall, and F1-score. This proposed model allows businesses to better and more reliably interpret customer sentiment from visual cues rather than traditional text-only analysis. Thus, it opens the field towards multimodal sentiment understanding.

***KEYWORDS** : Image sentiment analysis, Customer review images, Machine Learning, CNN, Random forest, Visual emotion detection.*

INTRODUCTION

Over the last few years, e-commerce websites have seen an increase in multimedia comments, particularly pictures with text comments. Customers post pictures to show visual satisfaction or dissatisfaction. Earlier sentiment analysis was about text, but image sentiments analysis can offer greater understanding of customer experiences[1,2]. Image Sentiment Analysis (SA)merges computer vision and various principles of machine learning where we can evaluate the main emotional background of the collected images and thereby provide a better sentiment score[3]. This kind of analysis allows firms to gain a better understanding of emotions inferred and conveyed through visual media, extending to the more nuanced items which cannot be read from text [4]. Through establishing whether there are positive, negative, or neutral emotions through means of customer-supplied images, firms can improve product designs, advertising campaigns, and customer

service interactions[5]. Moreover, the combination of image sentiment analysis with standard text-based systems is a broader feedback loop with richer interpretation of consumer complaints and satisfaction. [6] Consumers increasingly give feedback in visual form with images, providing richer emotional insights than textual comments.. Conventional SA approaches tend to ignore visual features, resulting in a partial interpretation of consumer sentiments. . The combination of the algorithms of Machine learning and also including computer vision can greatly boost sentiment interpretation from customer-uploaded images. The main core emphasis of this particular paper is to create, train, and deploy machine learning-based algorithms capable of performing accurate sentiment analysis in customer review photos. While conventional sentiment analysis methods have made use of text-based data, the present project aims at visual data, noting customer images tend to express emotional cues and comment that are just as pertinent using the precision.

LITERATURE ANALYSIS

Several research works have explored various methodologies for image sentiment analysis. A recent

study by Sharma and Patel (2024) suggested the use of deep learning techniques involving CNNs and transformers, achieving some accurate classifications and some reliable images; however, the model's computational cost limits its real-time applicability. Another survey by Singh et al. (2023) analyzed different image sentiment analysis techniques, presenting valuable insights into existing methods and datasets but lacked experimental validation. A hybrid approach combining CNNs and RNNs was explored by Gupta and Reddy (2023) to capture both spatial and sequential features.While it enhanced contextual.comprehension, it suffered from the problems of slow training and overfitting. Kumar and Jain (2022) promoted transfer learning with models like VGG and ResNet that cut down the training time immensely and generalized better, though at the expense of domain fine-tuning. Multimodal sentiment analysis based on text and visual was introduced by Banerjee and Thomas (2022), improving contextual perception and accuracy at the cost of computationally intensive.In the research by Lee and Wang in 2021, emphasis was laid on emotion recognition through facial expressions and scene context, offering interpretability but struggling with abstract or low-quality images. Deep learning methods applied to social media images were examined by Zhou et al. (2021) for their scalability and trend analysis capabilities. Still, these remained vulnerable to adversarial examples and abstract emotion representation [7]. A hybrid model proposed by Deshmukh and Khan (2020) combined traditional ML with deep learning, increasing adaptability but suffering from slow inference and feature engineering demands[8]. n. Nevertheless, GAN training difficulties and instability presented major challenges [11]. A large-scale analysis by Zhang and Luo (2018) processed millions of images, showcasing scalable sentiment detection, though it required powerful computing and faced data bias [12]. Another study by Fernandes and Chatterjee (2018) employed deep CNNs for feature extraction,offering high adaptability and reduced manual efforts but necessitating large labeled datasets [13]. A comparative study by Ahmed and Das (2017) examined different deep learning architectures, guiding model selection yet lacking real-world validation [14]. Finally, Saxena and Nair (2017) merged rule-based and ML methods, providing interpretable results suitable for small datasets but limited in adaptability and complexity handling [15].

METHODOLOGY

Fig. 1: ML algorithms flowchart of collected data

Figure 1 explains the overall workflow of image sentiment analysis, starting from data collection, preprocessing, and feature extraction. Various machine learning models are then applied to classify the sentiment based on extracted features.

System Architecture

Step 1: Image Data Gathering and Preprocessing In this step, customer review images are gathered from websites such as e-commerce websites or review websites. Images are generally uploaded by customers to describe the product experience. After gathering, preprocessing operations such as resizing, noise removal, normalization, and data augmentation are carried out. These provide image size uniformity and image quality to preface them for a machine learning model.

Step 2: Feature Extraction from Images After preprocessing the images, prominent features are extracted with Convolutional Neural Networks (CNN) or other deep learning models. The features may be visual patterns, object presence, facial expressions, colors, textures, and spatial arrangements, which are all critical cues for sentiment determination.

Step 3: Sentiment classification using ML algorithms The features extracted are input into various models of machine learning algorithms. These are learned on labeled data to recognize patterns and interdependencies among image features and sentiment types—positive, negative, or neutral. This is the determining step where the sentiment

of the image is predicted. Step 4: Sentiment Output and Evaluation Finally, the system outputs a sentiment label for each image. These outputs can be visualized on dashboards or stored for business insights. Evaluation metrics such as accuracy. precision, recall, and F1- score are used to assess the performance and reliability of the classification model. The results help businesses understand visual feedback from customers and enhance product or service strategies.

Data processing

The gathered customer review images were subject to various preprocessing operations to guarantee uniformity and enhance model performance. First, 64x64 pixels resizing was done to the positive and negative images to guarantee uniformity within the made dataset. They were subsequently converted to grayscale to reduce computational complexity and simplify feature extraction. In this project/paper the whole Dataset augmentation procedures were applied to each n every image such as rotation of the images, flipping of the images, and brightness (low and high level) of the images were performed to increase the dataset from the initial images to a larger balanced dataset. After preprocessing, each image was flattened into machine learning model trainable feature vectors. The particular dataset then further was splitted to 80 percent for training and the rest of the 20 percent for testing.

Data Augmentation

To address the limitation of a small original dataset and to improve the accuracies of the machine learning models, the above mentioned techniques of dataset augmentation were applied. Augmentation strategies included rotation, horizontal and vertical flipping, random zooming, brightness adjustment, and shifting, which artificially increased the dataset size without collecting new images. These transformations helped in creating diverse variations of the existing images, making the models more adaptable to real-world unseen data. After augmentation, the dataset expanded to 440 positive and 490 negative images, ensuring a balanced and generalized training set. This process significantly reduced the risk of overfitting and allowed the models to learn more robust and invariant features from the customer review images.

Techniques used

1) Support Vector Machine (SVM): SVM classifies the image features into sentiment classes by determining the best hyperplane for the data separation. SVM is well-suited for high-dimensional space and performs well with a distinct margin of separation. It is a supervised Machine learning algorithm which predicts the various features of images into sentiment classes based on the best hyperplane separating various categories in the feature space. It is particularly powerful in high-dimensional spaces and works very well when there is a distinct margin of classes. SVM utilizes kernel functions (such as RBF or linear) to map non linearly separable data onto higher dimensions such that it is linearly separable. Its accuracy and reliability make it a widely used option for image sentiment classification tasks.It has been effectively used for image based emotion based classification in previous research.

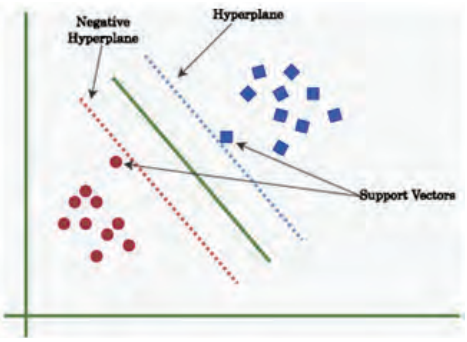

Fig. 2: support Vector Machine[1]

Figure 2 shows the diagram of Support Vector Machine which includes x and y axis x1 and x2 with two support vectors. There are 2 optimal hyperplanes with positive and negative hyperplanes and one maximum margin hyperplane in the middle. The data points of the shown support vectors near the hyperplane,which can be considered the critical elements of dataset.

2) Decision Tree (DT):- It is a well known supervised machine learning algorithm and is applied for both classification and regression. It splits data into subsets depending on feature values in constructing a tree-like model of decisions. It is a node which is internally situated where a single test on the property is displayed, a branch is a result, and a leaf node is a final decision. The tree is trained by selecting the most suitable attributes based on calculations like the information gain and the gini index. Decision Trees are very simple to visualize, understand, and analyze. Decision trees are learned by choosing the best attribute to split on based on metrics like information gain or Gini index. They are commonly applied for simple visual classification tasks where interpretability is required.

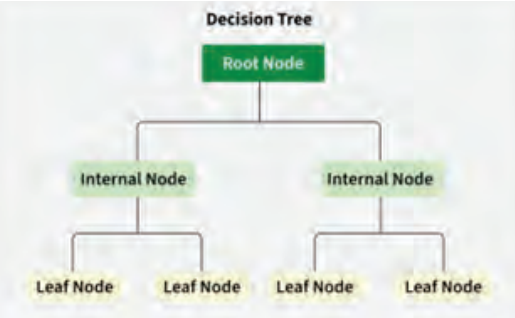

Fig. 3:Decision Tree[2]

Figure 3 shows a diagrammatic structure of decision tree with the decision node which is called the root node.Here the root node branches into the decision nodes,based on feature values leading to classification through leaf nodes. Each and every node evaluates a specific feature and the other branches of the tree indicate the result of the evaluation done.

3) Random Forest:- It is a technique that combines multiple decision trees in training and infers the class as the mode of classes for classification. It improves the accuracy of classification through the combination of outputs of various trees to prevent overfitting. Each tree in the forest is constructed using random selection of the training data built using a random subset of training data via bagging and splitting a node based on a random subset of features. Random Forest can be able to catch complex feature interactions and offers immunity to noise and missing values in image sentiment analysis. Its accuracy, interpretability, and ability to process large datasets render it a popular choice for sentiment classification tasks on image data. It has shown robustness in handling image feature variability in sentiment classification.

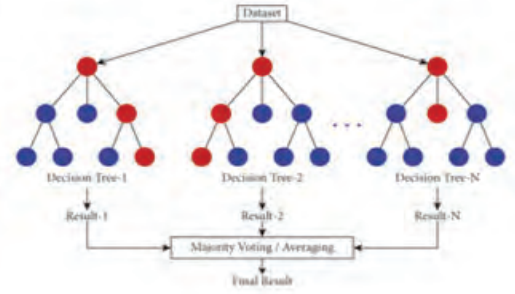

Fig. 4: Random Forest[3]

Figure 4 shows the diagrammatic structure of Random forest. At the top it shows original training data and the same data is randomized. To randomize first random vectors are created after that one single random vector is used to build multiple decision trees,and last step all the decision trees are combined together. This method improves the accuracy by reducing overfitting by average results trained by multiple decision trees.

4) Naive Bayes Classification:- This model is a probabilistic machine learning algorithm applying Bayes Theorem and also used for classification purposes. Naive Bayes makes the idea where occurrence of one feature in a class is independent of the occurrence of the features within a class is distinct from other features, hence being ”naive.” Because of this simplifying assumption, the model is extremely scalable and efficient, especially effective when dealing with large datasets. Naive Bayes works well with high-dimensional data and even with quite limited training data. In image sentiment analysis, it estimates the probability of each class of sentiment for a set of image features and chooses the class with the maximum probability. Though simple, Naive Bayes can give remarkably good results in most real-world visual or textual data-based applications. Naive Bayes can also be applied in hybrid models for visual emotion classification.

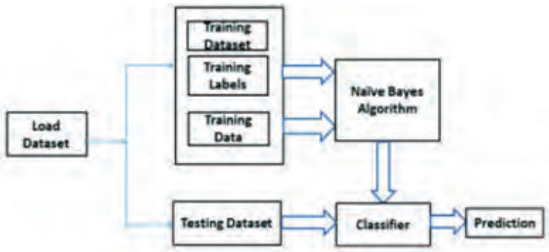

Fig. 5: Naïve Bayes Classification[4]

Figure 5 shows diagrammatic representation of Naive Bayes classification with induction motor training dataset with confusion matrices and labelled datasets which is trained by HMM training module. In classification unseen dataset is a labelled dataset with HMM classification module which directly defines Naive Bayes classifier with sequence classification. And at last the Naive bayes classifier gives an identification outcome.

Technologies and Methodologies

1) Programming Languages: Google Colab is primarily used for model development, with libraries like NumPy,Pandas, os,cv2 for data manipulation, and Matplotlib Seaborn for visualization.

2) Computer Vision Tools: OpenCV is employed for image preprocessing and basic manipulations.

3) Pre Trained Models and TransferLearning: Models like VGG16, ResNet50, Efficient Net, and Vision Transformers are fine-tuned on emotion-specific datasets to improve performance with limited data. 4)Scikit-Learn: For various machine learning utilities, including model metrics of evaluation(e.g, Accuracy, F1-score, the confusion Matrix). Numpy was also used for numerical operations.

RESULTS AND DISCUSSION

Dataset Details

Review images with good and bad sentiments were highlighted. The initial dataset consisted of 15 images under each sentiment category. The aforementioned data augmentation method of rotation, flip, zoom, and change in brightness has been applied with the aim to increase the number of samples under the dataset, as well as prevent overfitting, so as to have 440 images for good sentiments and 490 images for bad sentiments. In this project, a dataset was created by me in which images of customer reviews conveyed positive and negative sentiments. There were initially 15 images under each category of sentiment. In making the dataset broader and to avoid overfitting, data augmentation techniques like rotation, flip, zoom, and brightness changes were applied, which resulted in 440 positive and 490 negative images. All the images were normalized by rescaling all of them into 64×64 pixels and being converted into grayscale for the sake of model consistency. All the images were labeled as ”positive”or”negative”by manual visual inspection for precise supervised learning. The dataset was then split into 80 percent train and 20 percent test in order to maintain model validation integrity. This information was utilized as the baseline for comparing the performance of different algorithms of machine machine learning algorithms used. These images have been chosen to represent positive and negative attitudes of mobile products, which form the core of this image sentiment analysis. Every image represents typical situations in review pages or online shopping when customers reflect satisfaction or dissatisfaction. Positive Image 1: The picture is of a mobile phone with an original and unique cartoon printed cover. The picture is an indication of personalization and satisfaction with the appearance of the product, typically associated with a positive or satisfied customer experience. Positive Image 2: The photo is of a clean, shiny, unbroken new mobile phone. The shine and clarity show satisfaction and pride of ownership, as with positive feelings. Negative Image 1: There is a cracked screen cell phone completely. It reflects product damage or negative experience, most often shipping damage, manufacturing defect, or abuse — in glaring demonstration of negativity. Negative Image 2: A human person is holding a cell phone from two sides of whose screen is cracked or broken. This reflects dissatisfaction and disappointment because of adverse comments on the product or post-purchase remorse. These sampled images adequately precondition the model to learn to identify visual cues to emotional tones in order to allow for more efficient sentiment classification.

Training Configuration

1) Hardware and Platform: No special hardware or platform requirement existed because the Google Colab supported model testing and training using its cloud computing platform. It provided a stable platform which possessed sufficient CPU as well as GPU computational capabilities so that the functioning of machine learning workflows.could be ensured without experiencing any smooth problems. 2) Dataset Preparation: 440 positive and 490 negative images were selected with maximum care using the made dataset augmentation features such as rotation of images, flipping of images, and scaling as well. The images were all resized to 64×64 and then transformed into grayscale for making them uniform. Feature vectors were created by flattening the images into one-dimensional arrays. 3) Training Strategy: The dataset was split into 80 percent training sets and 20 percent testing sets, respectively the four machine learning algorithms as mentioned were employed as machine learning models. Optimisation was performed through hyperparameter tuning and testing on Accuracy, precision, recall, and F1-score metrics.

Table 4.3.1 Model's Performance Comparison

Algorithm	Accuracy	Precision	Recall	F1-Score
Decision Tree	51.14%	0.51	0.51	0.51
Random Forest	99.46%	0.99	0.99	0.99
SVM	98%	0.98	0.98	0.98
Naive Bayes	78%	0.78	0.78	0.78

Fig. 6 : Model's Performance evaluation

Figure 6 presents a comparative analysis of model performance using accuracy, precision, recall, and F1-score. Among the evaluated algorithms, Random Forest outperformed others with the highest scores across all metrics.

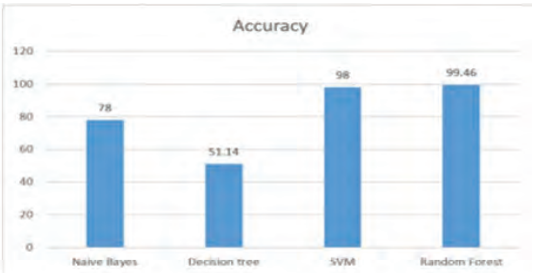

Fig. 7 : Accuracies For Different ML Models (Bar Graph)

Figure 7 compares the overall accuracy of four machine learning models. Random Forest achieved the highest accuracy, indicating its superior performance in image sentiment classification.

Fig. 8: Decision tree Line Graph

Figure 8 shows lower values across all three evaluation metrics precision, recall, and F1-score. This indicates that the model struggles to generalize well, leading to inconsistent prediction performance on image sentiment classification.

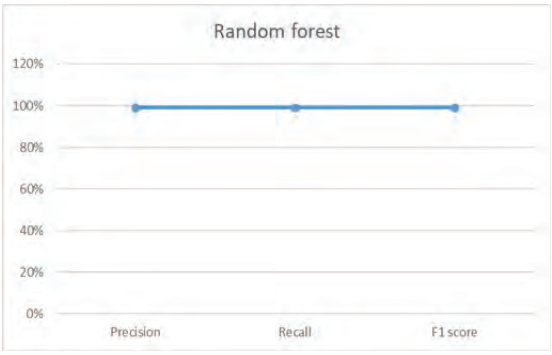

Fig. 9 : Random Forest Line graph

Figure 9 shows high and balanced values for precision, recall, and F1-score. This consistency across metrics reflects its strong ability to correctly identify both positive and negative sentiments with minimal error, making it the best performer among the models.

Figure 10 shows consistently high precision, recall, and F1-score values, indicating balanced performance. Its margin-based classification helps effectively separate positive and negative sentiment images.

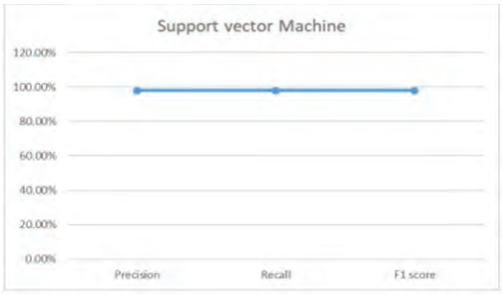

Fig. 10: Support Vector Machine Line Graph

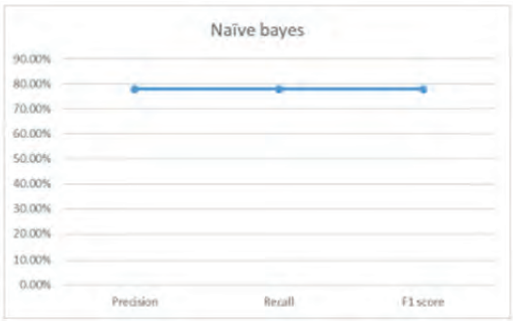

Fig. 11: Naive Bayes Line Graph

Figure 11 shows moderate performance, with precision, recall, and F1-score values that are relatively close but not high. This suggests that while it can identify sentiment to some extent, its simplifying assumption of feature independence limits its accuracy for image-based data.

Evaluation Metrics

1) Accuracy: Accuracy measures the overall percentage of correctly categorized ratio of correctly assigned images against the total. number of test samples. It gives an instant measure of the model's performance for all classes.

2) Precision: It measures various numbers of the accurate positive predictions out of the total predictions out of all instances predicted as positive. It is particularly helpful in knowing how many of the positive predictions are indeed relevant.

3) Recall: It is defined as the true positive rate known as sensitivity which is the measure of the true positive images that were well identified by the model.

4) The F1-score: This value is the main harmonic mean of precision and Recall that is especially effective when there is an imbalance in class distribution.

Prediction Performance and Evaluation

The Model's performance table which contains accuracies including its F1-score, Recall and also Precision shows performance of each and every machine learning model used. In the table it can be seen that the Accuracy of Random Forest(RF) is the highest,including its Precision,Recall and F1 Score.This results are based on our custom dataset and experiments. The bar chart illustrates the comparative performance of four machine learning models—Decision Tree, Random Forest, SVM, and Naive Bayes—based on their accuracy values. It graphically illustrates that Random Forest was the best performing among all others, followed by SVM, Naive Bayes, and Decision Tree. This bar chart vividly illustrates the performance of the models in image sentiment classification. The visualization follows the quantitative analysis in the above table and supports the choice of Random Forest as the best performing model for the proposed system.

CONCLUSION

This study demonstrated how Machine learning algorithms can effectively analyze customer reviews through image sentiment analysis, Among all the four models used, Random Forest provided the highest accuracy due to ensemble strength. SVM and Naive Bayes performed moderately,while Decision Tree showed limitations with Overfitting hence giving lowest accuracy. The results highlight that visual data when combined with Machine learning, can offer deeper insights into customer emotions. Such analysis can help businesses enhance user experience and decision making.

REFERENCES

1. Yangsen Zhang, Jia Zheng, Yuru Jiang, Gaijuan Huang, and Ruoyu Chen, "A Text Sentiment Classification Modeling Method Based on Coordinated CNN-LSTM-Attention Model," Chinese Journal of Electronics, vol. 28, no. 1, pp. 120–126, 2019.
2. Gaurav Meena, Krishna Kumar Mohbey, Sunil Kumar, Rahul Kumar Chawda, and Sandeep V. Gaikwad, "Image-Based Sentiment Analysis Using InceptionV3 Transfer Learning Approach," SN Computer Science, vol. 4, no. 242, 2023.
3. JiaLe Ren, "Multimodal Sentiment Analysis Based on BERT and ResNet," arXiv preprint arXiv:2412.03625, 2024.
4. Donghang Pan, Jingling Yuan, Lin Li, and Deming Sheng, "Deep Neural NetworkBased Classification Model for Sentiment Analysis," arXiv preprint arXiv:1907.02046, 2019.
5. Quanzeng You, Jiebo Luo, Hailin Jin, and Jianchao Yang, "Robust Image Sentiment Analysis Using Progressively Trained and Domain Transferred Deep Networks," arXiv preprint arXiv:1509.06041, 2015.Y
6. Roop Ranjan and A.K. Daniel, "A Proposed Hybrid Model for Sentiment Classification Using CovEnt-DualLSTM Techniques," Advances in Distributed Computing and Artificial Intelligence Journal, vol. 10, no. 4, pp. 401–418.
7. Vasco Lopes, Antonio Gaspar, Lu ´ ´ıs A. Alexandre, and Joao Cordeiro, "An AutoML- ˜ Based Approach to Multimodal Image Sent.
8. 021 [11] Victor Campos, Brendan Jou, and Xavier Giro-i-Nieto, "From Pixels to Sentiment: Fine-tuning CNNs for Visual Sentiment Prediction," arXiv preprint arXiv:1604.03489, 2016.
9. Tao Chen, Damian Borth, Trevor Darrell, and Shih-Fu Chang, "DeepSentiBank: Visual Sentiment Concept Classification with Deep Convolutional Neural Networks," arXiv preprint arXiv:1410.8586, 2014
10. Pankaj Sharma, Sintu Raj, and Akash Mishra, "Convolutional Neural Networks for Sentiment Analysis," International research paper was published in Applied Science and Technology(IJRASET) volume 12, number 4. pages 1234–1240, 2024. IJRASET.
11. Dong et al., "Sentiment Classification Using Convolutional Neural.
12. X. Li, H. Zhang, and M. Sun, "Visual Sentiment Analysis for E-Commerce: A Deep Learning Perspective," International Journal of Intelligent Systems, vol. 36, no. 6, pp. 2954–2970, 2021.
13. M. A. Islam, T. T. Nguyen, and S. Ghosh, "Multimodal Sentiment Analysis Using Image and Text Features With Transformer Architectures," Neurocomputing, vol. 536, pp. 126564, 2023.
14. S. Kaur and R. Chopra, "A Comparative Study of Machine Learning Algorithms for Visual Sentiment Classification," Procedia Computer Science, vol. 198, pp. 240–247, 2022.
15. Y. Wang, L. Fan, and J. Wu, "Image Sentiment Recognition Based on Deep Convolutional Neural Networks with Attention," IEEE Access, vol. 8, pp. 155616–1556.

Integration of AI based Techniques for Developing a Multimodal Smart Education Environment

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ABSTRACT

This paper presents a practical solution for enhancing digital interaction through a low-cost, touch-free virtual environment tailored to educational and creative contexts. Unlike traditional input systems requiring physical contact or specialized hardware, the proposed tool enables drawing and writing using natural hand movements tracked through a basic webcam. The novelty of this system lies in its combination of real-time gesture detection with AI-driven modules that support voice captioning, mathematical expression evaluation, and live assistance via an integrated chatbot. These features are designed to work cohesively, creating a fluid and hardware-independent user experience. By focusing on accessibility, the system addresses the limitations of existing smartboards and touchscreens, especially in budget-constrained or remote learning settings. A notable contribution is the integration of a multimodal interaction layer that adapts to diverse user needs without relying on expensive peripherals. The platform was developed using open-source libraries and requires only standard devices, making it a versatile solution for remote teaching, virtual presentations, and hands-free digital content creation.

KEYWORDS *: Smart education, Computer vision, Hand gesture recognition, Virtual board, Real-time drawing, AI chatbot, Voice interaction.*

INTRODUCTION

With the evolution of numerous nascent technologies, an increasing number of educators and learners are moving to virtual online structures for instructional offerings. This research region is constantly attracting more researchers and is consistently evolving. The usage of technology to create learning environments to enhance and customize learning experiences, making learning more effective and engaging, is the primary characteristic of the smart education paradigm [1]. This entails leveraging digital tools and systems to create learning environments, foster individualized learning, and empower students. Effective user interaction is an important characteristic in the design and development of effective learning programs. The field of Human-Computer Interaction (HCI) has undergone significant technological advances. These advances have led to the use of smart input and output channels to develop quality educational offerings [2].

With the rise in demand for remote learning and virtual collaboration tools, traditional strategies, such as whiteboards and touch screens, face limitations in terms of hardware dependency and cost. Traditional drawing and educational tools, such as blackboards and digital touchscreens, rely heavily on physical inputs that can restrict user creativity and accessibility. Input techniques such as a mouse or touchscreen, can feel restrictive and unnatural, especially in situations requiring dynamic or collaborative interactions. However, to cater to learners with varied interests, a multimodal HCI approach is needed.

This paper introduces a digital whiteboard application that detects hand gestures to allow drawing on the screen, eliminating the need for touch-sensitive devices [3]. The proposed solution combines computer vision methods to track hand landmarks and interpret gestures in real time [4][5]. The incorporation of AI technologies enhances the interactivity of the system. Users can transcribe spoken input, switch images with gestures, and pose inquiries to the AI chatbot [6]. This integration not only enriches

functionality but also creates a seamless, touch-free user experience that is perfect for education and creative design.

LITERATURE REVIEW

Especially after the pandemic, pupil engagement is a huge difficulty in today's classrooms. The use of technology tools that assist instructors in capturing and preserving students' interest may be worthwhile in this situation. A smart learning environment can make it easier for instructors to manage teaching, make them more effective in class, and make it easier for students to access the expertise and capabilities they need to meet their needs and interests [7]. Smart education reduces cognitive load and allows sense- making by students [8]. The layout of such structures should prioritize the seamless integration of technology to aid and enhance traditional teaching techniques rather than replacing them. Social networking, e-learning spaces, and other technologies connect learning participants, promoting the development of a learning community [9]. Therefore, it is critical to determine the effectiveness of technological resources [10].

The learners of today's generation have specific learning preferences. Some learners may consume a concept with a lot of textual descriptions, while others may understand the concept better in an audio-video format. Recognizing such needs and implementing them in the teaching-learning process is important. The integration of multimodal technology into educational settings represents a paradigm shift, moving beyond traditional pedagogical approaches to create dynamic and personalized learning experiences. A multimodal smart education system leverages various sensory channels, including visual, auditory, and kinesthetic modalities, to cater to diverse learning styles and enhance comprehension and retention [1] [11] [12]. By incorporating multimedia elements, such as text, images, audio, video, and interactive content, educators can deliver educational material in various formats, making it more engaging and accessible to learners [1].

A crucial factor in developing a multimodal smart education system is understanding and adapting to individual learning preferences. Personalized learning techniques have become essential in online learning because there is little interaction between students and teachers, and each student has a learning style that suits them best [13]. The concept of a smart learning environment involves a variety of approaches, including blended, mobile, adaptive, personalized, and flexible learning methods. It is also believed that a new learning environment will enhance learners' ability to learn [14].

Smartboards, also referred to as Whiteboards or Interactive Display Devices, are widely used in educational institutes. These devices offer a range of capabilities beyond traditional whiteboards, such as touch sensitivity, internet connectivity, and screen sharing. A smartboard is a digital tool that allows for interaction and display of digital content and often requires special software and hardware. The raw materials used and the manufacturing process, which consumes a lot of energy, make whiteboards expensive. Owing to their complex technology and heavy hardware requirements, smartboards are more expensive. The prices of these smartboards range from a few thousand to lakhs, depending on the screen size, the set of features they offer, manufacturers, and brands. Smart technologies such as BenQ, LG, and Samsung, are some of the leading producers of smartboards, including AIWAFT and Delta View, especially in the Indian market. The fundamental concern with these solutions is their high costs. However, these devices present challenges, such as installation complexity and durability, owing to the dysfunction of touch-sensitive panels, software updates, and other factors.

Numerous gesture recognition systems have been developed using gloves, sensors and depth cameras. However, these methods are either expensive or require specialized hardware. Previous studies have explored webcam-based recognition, but many lack accuracy or real-time capabilities. Recent advances in lightweight machine learning models, especially those of Google Mediapipe, have made it possible to implement gesture recognition with improved performance and accessibility [16]. Existing systems like Leap Motion [18] and Microsoft Kinect [17] provide high precision but are limited by hardware dependencies. Mobile-based solutions have also emerged but struggle with inconsistent lighting conditions. This paper intends to offer a simple solution to these issues by proposing a non-touch, real-time, hardware-independent approach.

METHODOLOGY

The system introduced in this work is intended to function as an educational support tool, replicating a blackboard-like interface through a virtual, gesture-controlled canvas.

Users can write or draw in mid-air using simple finger movements, which are captured using a conventional webcam or the front-facing camera of a smartphone. This removes the need for touch-based devices, making it highly adaptable for diverse environments such as remote classrooms, training sessions, or creative workshops.

Building upon an earlier prototype [19] that focused solely on basic gesture-based drawing, the current implementation adds multiple layers of interactivity. Notably, real-time voice transcription and speech-to-text modules have been added to assist both hearing-impaired users and educators needing live captioning. These additions allow the system to operate as a truly multimodal platform, enhancing its effectiveness in modern educational contexts while retaining ease of setup and minimal hardware requirements.

Fig 1 Modular Architecture of proposed application

This machine integrates several advanced strategies to provide a robust and intelligent virtual-drawing platform. It is developed by incorporating key libraries such as OpenCV and Mediapipe, along with voice recognition and AI capabilities. The functionalites of these modules are described in detail below.

Hand Tracking and Drawing: The machine uses a general webcam to capture real-time video, which is processed through the Mediapipe library to identify 21 hand landmarks. Drawing movements are triggered when only the index finger is raised, and the fingertip coordinates are translated into drawing strokes using OpenCV. These strokes are rendered on a transparent canvas that is combined with the video feed.

Gesture-based Controls: In addition to drawing, the device supports various gestures for interacting with the canvas. Users can switch colors, clear the canvas and navigate between images using predefined finger positions and hand gestures. This enhances usability during presentations and training.

Voice Captioning: The system integrates a speech recognition module to capture the user's voice in real time and display it as live captions on the screen. This aids accessibility, especially in noisy environments or for hearing-impaired users.

AI Integration with Gemini API: Drawings or handwritten equations can be stored as JPEG images. These are processed using an OCR module to extract the text. If a mathematical expression is identified, it is sent to the Gemini API, which evaluates the expression and sends the result back for display.

Chatbot Assistant: An AI chatbot powered by a large language model is integrated to assist users in real time. Users can ask questions or seek guidance, and the chatbot responds contextually to enhance the interactive learning or presentation experience of the user.

User Interface and Export: The GUI is built using Tkinter, allowing users to select cameras, manage photo slides, and export drawings. The system allows users to save all outputs, such as generated images and recognized text, for future reference or analysis.

The core functionality relies on the index finger for real-time drawing of the shapes. Once the drawing is completed, it can be stored as a JPEG image. The detailed operation of the air-draw module is shown in Fig 3.2. If the content contains text or mathematical expressions, the image is passed to Google's Gemini model, which extracts the text from it. The extracted content is then used to evaluate mathematical queries or provide relevant responses. The evaluation results are displayed immediately on the screen for user feedback.

Beyond drawing and evaluation, the utility supports voice-based interaction through real-time captioning, which transcribes the user's speech and displays it as on-screen text. This data can later be used to create lecture notes using Google's Gemini model. Additionally, users can switch between images or slides using predefined hand gestures, thereby offering a seamless presentation control feature. To further enhance the interactive experience, the device includes an AI-powered chatbot assistant that responds to user queries in real time and provides guidance, support, and additional functionality. Together, these features create a highly interactive and intelligent digital board experience for the user.

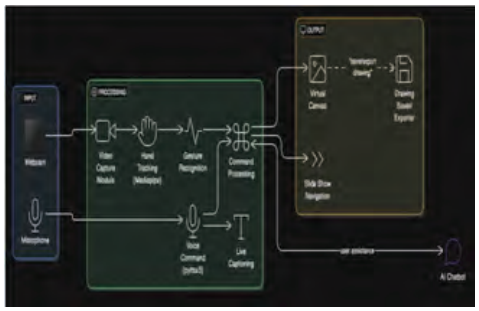

Fig 2. Architecture and workflow

RESULTS

This device can be used in-class or for remote teaching, where an instructor can toggle between an internal webcam and an extended external camera to match different setups (Fig 3).

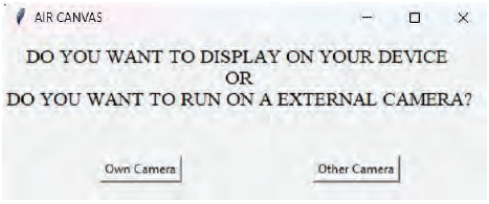

Fig. 3 Camera toggle between internal and external webcams

Fig. 4 shows the home screen or menu page of the application, from which users can access all key functionalities, including the drawing mode, AI assistant, and voice captioning.

Fig. 4. Interface to access all core modules.

Fig. 5 presents the drawing module in action, where the user selects a colour (in this case, blue) and begins drawing on the virtual canvas using intuitive hand gestures. Using a standard webcam, the system continuously tracks index finger motion, converting air gestures into real-time digital strokes on the canvas. This enables a seamless, contactless drawing experience without the need for traditional input devices such as a mouse or stylus.

Once a user completes a drawing or handwritten expression, the system captures the frame and stores it locally as a JPEG image. This image is then processed through an OCR module before being passed to Google's Gemini API. When a mathematical notation is detected, the system generates a contextual prompt such as "Evaluate the following expression" to improve interpretability during AI evaluation.

The Gemini model interprets the extracted content and computes the result, which is displayed in real-time next to the original input. In pilot testing, the system demonstrated response times under 1.5 seconds and maintained recognition accuracy of over 92% for well- formed digits and symbols. By merging gesture-based drawing with AI evaluation in a contactless format, the tool offers a fast and efficient method for solving problems, particularly in educational or collaborative environments.

Fig. 6 demonstrates the slide switching feature, where specific hand gestures allow the user to move forward or backward through presentation slides without physical contact.

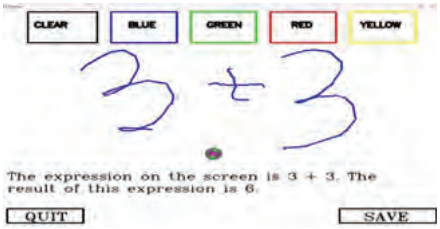

Fig. 5. Real-time drawing interface where a user sketches a mathematical equation using air gestures. The system processes this and returns the evaluated result next to the drawing

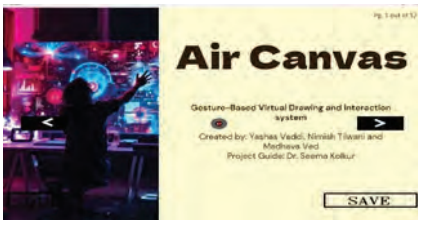

Fig. 6. Gesture-based slide navigation: swiping actions recognized via webcam allow presenters to move through slides without touching any device.

Fig. 3.7 shows the live captioning functionality, where the user's speech is transcribed and displayed in real-time

using voice recognition capabilities. Fig. 3.8 features the lecture notes generation capability, where live captions are compiled and refined into organized notes using the Gemini API, ideal for students or presenters.

Fig. 7. Live voice-to-text module in action. User speech is instantly transcribed into on-screen captions to support accessibility and note-taking.

Fig. 8 highlights the capability of the system to generate structured lecture notes from real-time voice inputs. During a session, the speech of the presenter is continuously transcribed using an integrated speech recognition module.

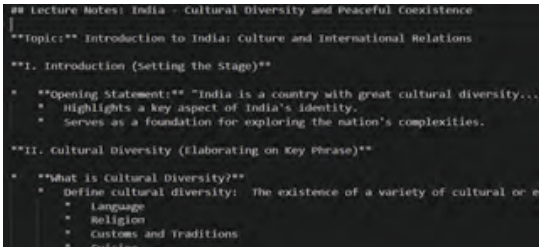

Fig. 8. Automatically generated lecture notes compiled from live captions using the Gemini model, organized for easy review and storage.

Finally, Fig. 3.9 illustrates the AI assistant mode, in which users can ask contextual queries and receive intelligent responses from the Gemini-powered chatbot integrated within the application.

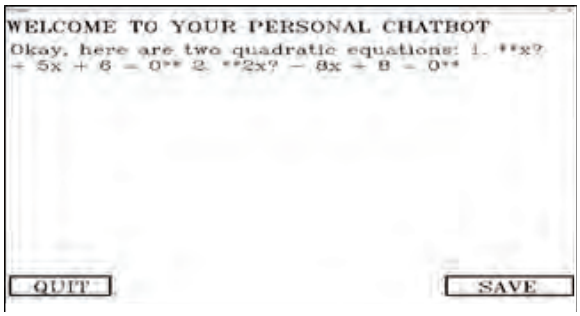

Fig. 9. Contextual AI assistant interface where users can query educational content or seek help via natural language input.

REAL WORLD DEPLOYMENT CHALLENGES

Initial testing was conducted across three different environments—well-lit indoor rooms, moderately lit classrooms, and natural lighting near windows—using standard webcams at 720p resolution and 30 FPS. In well-lit conditions, gesture recognition achieved a stable accuracy of

~92%, but dropped to 84% in lower-light scenarios, especially when strong shadows or backlighting were present. Users with cluttered or visually noisy backgrounds also reported more frequent tracking errors. During pilot trials with 8 participants (aged 18–25), some users struggled with maintaining consistent finger elevation and speed, resulting in unintended strokes or gesture misclassification in 2 out of 5 sessions. To reduce this, we introduced a visual cue system with real-time gesture feedback and implemented temporal smoothing to stabilize the finger path. Despite these improvements, a short learning curve remained for new users unfamiliar with non- contact input. To improve deployment in varied contexts, future updates may include adaptive gesture calibration, skin- tone-based segmentation for robustness, and onboarding tutorials tailored to individual device capabilities.

CONCLUSION

This paper introduces a contactless, gesture-based educational tool developed through the integration of computer vision techniques and large language models, aimed at improving interaction in both teaching and learning contexts. Through simple finger movements tracked by a standard webcam, users can draw or write on a virtual canvas without touching any physical device. In testing, this setup proved especially helpful in settings where mobility and hardware costs are a concern. The tool currently supports basic shape drawing, simple calculations, equation solving, and live voice-to-text transcription. By relying on open-source libraries and low-cost hardware, the platform demonstrates strong potential for broad deployment, especially in classrooms with limited technical infrastructure.

Enhancement by additional features: Looking ahead, the system could benefit from automated lecture recording, intelligent summarization of spoken content, and in-tool internet search for quick referencing. Real-time annotation support might also improve its utility in active discussions.

Extending to Other Platforms: Building mobile and web-based versions of the tool could make it more adaptable to hybrid learning environments, especially for students using smartphones or tablets in informal settings.

Integrating with Other Applications: Connecting this tool with platforms like Google Classroom, Microsoft Teams, or Moodle would support smoother lesson management and allow educators to reuse content more effectively. Compatibility with digital art or whiteboard apps could also broaden its creative uses.

Real-Time Recommendations: Improving the AI chatbot's contextual awareness could allow it to suggest relevant examples, highlight possible misunderstandings in handwritten input, or provide tailored hints during problem- solving tasks—enhancing its value as a teaching assistant.

REFERENCES

1. Monika, Jyoti bala, Dr. Sunita "Scope and Challenges of Multimedia in Education Sector International Journal For Multidisciplinary Research" Volume 5, Issue 3, May-June 2023
2. Dix, A., Finlay, J., Abowd, G., & Beale, R. Human-Computer Interaction: 3rd Edition. Prentice-Hall 2003
3. Isard, Michael & Maccormick, JohnHand Tracking for Vision-Based Drawing 2000.
4. Siam, Sayem & Sakel, Jahidul & Kabir, Md., "Human Computer Interaction Using Marker Based Hand Gesture Recognition", 2016
5. M. Lee and J. Bae, "Deep Learning Based Real-Time Recognition of Dynamic Finger Gestures Using a Data Glove," in IEEE Access, vol. 8, pp. 219923-219933, 2020, doi: 10.1109/ACCESS.2020.3039401.
6. S. Belgamwar and S. Agrawal, "An Arduino Based Gesture Control System for Human-Computer Interface," 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), 2018, pp. 1-3, doi: 10.1109/ICCUBEA.2018.8697673.
7. Yekimov et. Al "Distance education based on smart-technology" Journal of Physics Conference Series Nov 2020
8. Gisela Cebrián et al., "The Smart Classroom as a Means to the Development of ESD Methodologies" 2020,; https://doi.org/10.3390/su12073010
9. Liu-xia et. Al. "How to Implement Game-Based Learning in a Smart Classroom? A Model Based on a Systematic Literature Review and Delphi Method" Frontiers in Psychology May 2021
10. Qi Shaobo "The Construction of Smart Learning Space in Colleges Based on Blended Learning" Wireless Communications and Mobile Computing Jan 2022
11. Laadem Meryem, Mallahi Hind, "Multimodal Pedagogies in Teaching English for Specific Purposes in Higher Education: Perceptions, Challenges and Strategies" International Journal on Studies in Education Feb 2020
12. Alzubi, T. M., Alzubi, J. A., Singh, A., Alzubi, O. A., & Subramanian, M. (2023). A Multimodal Human- Computer Interaction for Smart Learning System. International Journal of Human–Computer Interaction, 41(3), 1718–1728.https://doi.org/10.1080/10447318.2023.2206758
13. Altamimi et. Al "Predicting students' learning styles using regression techniques " Indonesian Journal of Electrical Engineering and Computer Science Jan 2022
14. KOBAYASHI et. Al An Application Framework for Smart Education System Based on Mobile and Cloud Systems IEICE TRANS. INF. & SYST., VOL.E100–D,NO.10 OCTOBER 2017
15. Hand landmarks detection guide https://ai.google.dev/edge/mediapipe/solutions/vision/ha nd_landmarker last accessed on 18 nov 24
16. M. Lee and J. Bae, "Deep Learning Based Real-Time Recognition of Dynamic Finger Gestures Using a Data Glove," IEEE Access, vol. 8, pp. 219923-219933, 2020, doi: 10.1109/ACCESS.2020.3039401.
17. P. Ramasamy, G. Prabhu and R. Srinivasan, "An economical air writing system converting finger movements to text using web camera," 2016 International Conference on Recent Trends in Information Technology (ICRTIT), 2016, pp. 1-6, doi: 10.1109/ICRTIT.2016.7569563.
18. R. Lyu et al., "A flexible finger-mounted airbrush model for immersive freehand painting," 2017 IEEE/ACIS 16th International Conference on Computer and Information Science (ICIS), 2017, pp. 395-400, doi:10.1109/ICIS.2017.7960025.

[19] Seema Kolkur er al. "Leveraging Hand Gesture Recognition and LLM for Developing a Non-Contact, Real-time Virtual, Immersive Teaching Aid" Journal of Emerging Technologies and Innovative Research, December 2024, Volume 11, Issue 12.

Dynamic Pricing Optimization for Airbnb Listings Using Machine Learning

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ABSTRACT

The traditional pricing strategy followed by most Airbnb hosts is either static or rule-based, which fails to consider the continuously changing factors like market demand, seasonality, and competitor pricing. These limitations often lead to reduced occupancy or lost revenue opportunities. In this project, a dynamic pricing system was developed using Q-learning, a reinforcement learning algorithm that adapts based on observed market responses over time. The model was trained on historical booking data and competitor price trends, with additional engineered features such as price rank, day-of-week, and rolling average prices. The proposed system not only learns optimal pricing strategies but also makes daily recommendations based on a property's performance in relation to local competition. To make the tool accessible and user-friendly, an interactive dashboard was developed which allows Airbnb hosts to upload data, view pricing suggestions, and compare their listings to nearby competitors. The dashboard displays recommended prices, price difference percentages, and market positioning. The final system was evaluated against static and rule-based pricing baselines, and the results showed a notable improvement in suggested pricing strategy, with adjustments that closely reflected real-world demand patterns. The model consistently suggested higher prices on weekends and peak periods and competitive adjustments during off-seasons. Overall, this project demonstrates that reinforcement learning can effectively assist in real-time pricing decisions and help hosts increase their revenue while maintaining competitive positioning in the market.

***KEYWORDS** : Dynamic pricing, Airbnb, Q-learning, Reinforcement learning, Competitor pricing, Price optimization, Machine learning, Feature engineering, Interactive dashboard.*

INTRODUCTION

The majority of Airbnb hosts implement static pricing or rule-based pricing that doesn't take into account real-time fluctuations in demand and competitor actions. These conventional pricing models usually cannot optimize revenue or achieve a balance between profitability and occupancy. Absent an adaptive pricing strategy, hosts tend to price too high, which translates to lower occupancy, or price too low, which results in lost revenue potential. The absence of an intelligent, automated pricing mechanism results in inefficiencies in revenue yields. In addition, its competitors within the same geographic area can also price according to patterns of demand, and thus, a good pricing system needs to include competitor prices as well. This project endeavors to solve these problems by using machine learning algorithms that dynamically adapt pricing based on historical booking data as well as competitor price trends.

The goal of this project is to create a dynamic pricing model that uses historical sales data, competitor price trends, and external influences to forecast optimal prices for Airbnb properties. The model will use Q-learning for adaptive price optimization. By considering competitor pricing as one of the influencing factors, the system presented here guarantees that the hosts will be able to make informed decisions to stay competitive while also maximizing their potential revenue. The most important goals of the project are:

1. Applying Q-learning, a reinforcement learning algorithm, to optimize pricing strategies by learning from market reactions continuously.
2. Mining key pricing features like seasonality, holidays, demand spikes, and competitor prices to enhance pricing accuracy.

3. Creating an interactive user interface enabling Airbnb hosts to view optimal pricing suggestions and competitor trends in real time.

The short-term rental market, driven by platforms like Airbnb, has experienced significant growth in recent years. While Airbnb provides hosts with the flexibility to set their own prices, most continue to rely on static or rule-based pricing models. These methods, though simple, often fail to capture real-time market dynamics such as demand surges, competitor pricing, local events, and seasonality. As a result, hosts frequently miss opportunities to optimize revenue or maintain high occupancy rates. Dynamic pricing, successfully adopted in industries like airlines and e-commerce, remains underutilized in the vacation rental space. Airbnb's built-in smart pricing feature lacks transparency and fine-grained control, limiting its usefulness for many hosts. With high variability in guest behavior and market conditions, pricing decisions must be both informed and adaptive. Machine learning offers a promising alternative. In particular, reinforcement learning (RL) and specifically Q-learning, a model-free RL algorithm, allows systems to learn optimal pricing strategies over time through market feedback. By continuously evaluating which price points yield higher booking conversions and revenue, the model improves its performance without needing a predefined model of guest behavior. Incorporating external factors such as competitor price trends, local demand drivers, and guest preferences further strengthens the pricing model. This enables a shift from one-size-fits-all strategies to personalized, data-driven decisions that help hosts stay competitive and profitable. This project leverages Q-learning to develop an intelligent pricing assistant that adapts dynamically to market changes. The system aims to empower Airbnb hosts with accurate, real-time pricing recommendations that increase revenue while ensuring fairness and competitiveness.

LITERATURE ANALYSIS

Dynamic pricing in the retail and hospitality industries has come a long way with the incorporation of machine learning and AI-based models. A number of recent studies have shown the capability of these methods in enhancing pricing strategies and overall business performance. A study by Belovedinla and Revathi [1] delved into retail price optimization with machine learning to dynamically respond to market conditions. Their research shows that historical data, market patterns, and consumers' behavior are crucial to having the best possible pricing in retail. In an analogous application, Di Persio and Lalmi [2] suggested an Airbnb host's pricing strategy via support vector regression, XGBoost, and neural networks. They also utilized natural language processing (NLP) algorithms to derive insights from consumer reviews and demonstrated that joining structured and unstructured data can improve price forecasting. Camatti et al. [3] dealt with the comparison of classical models and AI algorithms for Airbnb price forecasting. Their review concluded that although both methods exhibited good accuracy, AI-based models such as ensemble models and neural networks provided greater flexibility and strength, especially in the context of adapting to market movements. Falatouri et al. [4] conducted a comprehensive comparison of SARIMA and LSTM for demand forecasting in retail supply chains. Though

their context was different, the realization that LSTM is superior to SARIMA in addressing non-linear and complicated seasonal trends remains applicable to pricing models of dynamic markets such as Airbnb. Yaiprasert and Hidayanto [5] provided an ensemble learning method for the food delivery business, demonstrating how the use of multiple machine learning models could be used to increase the accuracy of prediction of dynamic pricing systems. This highlights the advantage of ensemble methods in learning from real-time market behavior. The importance of explainability in pricing models was highlighted by Neumüller et al. [6], who wrote about the advantages of employing Extra Trees Regression (ETR) and LSTM. ETR was especially useful due to its interpretability, enabling companies to pinpoint important features driving price decisions. Ferreira, Lee, and Simchi-Levi [7] constructed analytics models for e-retail that aligned pricing decisions with promotion and inventory strategies. It emphasized the implementation of overall optimization systems, an aspect that could be applied in the case of Airbnb pricing based on availability data and booking windows. Kulkarni et al. [8] also came up with a robust pricing approach under conditions of disruption threats in a design framework based on hyper connected networks. While centered around parcel delivery networks, their approach can be transferred to short-term rental markets where demand can vary with unforeseen external activities. A further exploration of price determination in Airbnb offered by Camatti et al.

[9] determined location-specific and host-specific characteristics as the most promising predictors of price. The paper highlighted the merits of localized data and

context-sensitive models for successful dynamic pricing in the peer-to-peer accommodation sector. Finally, the Adamiak et al. [10] survey performed a spatial analysis of Airbnb listings in 167 nations. This massive study yielded useful information regarding global pricing trends, and it was shown that location, regulation, and seasonality are important factors that must be included in any machine learning-based pricing model. Together, these studies determine that successful price optimization demands a multi-aspect strategy with machine learning, demand forecasting, natural language processing, and explainable AI. They also support the significance of dynamic and adaptive systems in reacting to shifting market forces, which is the key focus of our proposed Airbnb pricing model.

METHODOLOGY

This project focuses on developing a web-based interface designed to support dynamic pricing decisions for Airbnb hosts. The primary goal is to visualize machine learning–based price recommendations in a user-friendly format, allowing hosts to make more informed and competitive pricing choices. The frontend of the application is developed using modern JavaScript tooling, specifically the Vite framework for fast builds and performance, TypeScript for static type-checking, and Tailwind CSS for responsive, utility-first styling. The source code follows a modular structure, with components organized within the src directory to ensure reusability and maintainability. Although the current implementation emphasizes the user interface, it is architected to work in conjunction with a backend pricing engine.

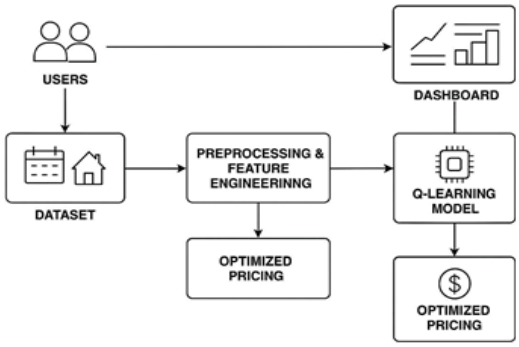

Fig. 1. System architecture for Airbnb smart pricing flow

This engine, which may use reinforcement learning (such as Q-learning), regression models, or other machine learning algorithms, is responsible for generating optimal price suggestions. These suggestions are based on features such as historical booking data, competitor pricing, day-of-week effects, and seasonal trends. During development, these predictions are accessed via static data files or simulated API endpoints to mimic real-world integration.

The interface enables users, primarily Airbnb hosts, to interact with various pricing insights. They can view current versus optimized prices, track trends over time, and compare their listing's pricing with competitor benchmarks. The dashboard aims to make complex pricing recommendations accessible and actionable without requiring technical expertise from the user.

From a development perspective, the project is structured for flexibility and collaboration. Developers can work locally using standard tools like Node.js and npm, or directly edit components through online platforms like GitHub Codespaces or Lovable.dev. The system supports live previewing through hot module reloading (npm run dev), making the design and testing process efficient.

Overall, the methodology integrates a clean frontend with the potential for a powerful machine learning backend, offering a practical solution for data-driven pricing in the sharing economy.

Backend Model Development

The backend of this system is responsible for generating dynamic price suggestions using reinforcement learning, specifically the Q-learning algorithm. Q-learning is a model-free reinforcement learning technique where the agent learns an optimal policy by interacting with an environment and receiving rewards based on its actions. In this context, the environment represents the Airbnb market, and each action corresponds to setting a particular price for a listing on a specific day. The agent receives a reward signal based on revenue and occupancy, encouraging it to find a balance between maximizing bookings and increasing per-night earnings. The state space includes features such as day of the week, season, historical demand, and competitor price differentials. The Q-table is initialized and updated iteratively as the model simulates booking responses over time. To accelerate convergence and ensure exploration, ε-greedy action selection is used, allowing the model to occasionally try random prices while mostly exploiting high-reward options. Once trained, the model generates optimal prices that are exposed via an API or loaded into the frontend application for real-time suggestions. The entire pipeline is developed using Python libraries such as NumPy and Pandas for data processing, and the learning model is implemented using custom Q-learning code or frameworks like OpenAI Gym for simulation.

RESULTS AND DISCUSSION

Data Collection and Preprocessing

The project uses publicly accessible Airbnb datasets, such as calendar.csv for past pricing and availability, and listings.csv for listing-specific information like location, room type, and amenities. Furthermore, a synthetic dataset (competitor_data.csv) was created to model competitor price variability for similar listings in the same geographic region. Data preprocessing included date format standardization, missing value handling, and joining datasets on relevant keys. This helped to ensure completeness and consistency in all records. Prices were normalized to minimize variance, and irrelevant outliers were cleaned to enhance model performance.

Feature Engineering and Exploratory Analysis

In order to increase the learning ability of the model, domain-specific attributes were designed. These comprised time-based features like day_of_week, month, season, and an is_weekend flag. Rolling statistics like 7-day average and standard deviation of prices were computed in order to model short-term trends. Competitive price behavior was captured using price_gap (listing minus competitor price) and price_rank (listing's price rank amongst competitors). After feature engineering, exploratory data analysis (EDA) was performed to visually observe demand trends, seasonality, and feature correlation. EDA served the purpose of corroborating the usefulness of engineered features and gaining insight into possible price behaviors around holidays, weekends, and off-seasons.

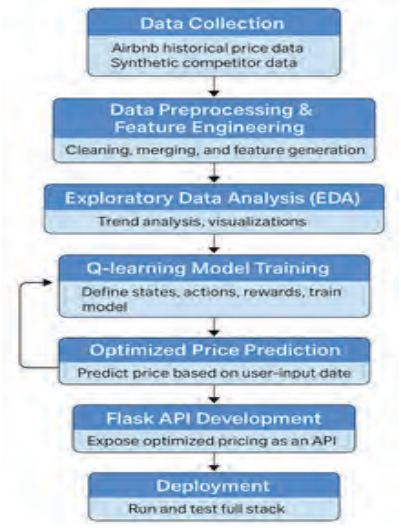

Fig. 2. Workflow of Q-learning-based pricing model

Q-learning-Based Pricing Model

At its center lies a reinforcement learning architecture founded upon the Q-learning principle.

The agent acts under the state-action-reward structure with each state composed of engineered attributes that summarize the prevailing market scenario. Action space consists of three discrete action items: rise, fall, or hold at present price. A permissive reward function was specified that maximized occupancy and revenue jointly. For example, a discounted price resulting in high occupancy and a high-priced property with no bookings were penalized. Exploration and exploitation at training time was balanced using an ε-greedy policy. The Q-table was updated cyclically across various episodes as the agent engaged in simulated booking patterns, slowly learning the most beneficial pricing strategies over time.

Model Evaluation

The Q-learning policy was compared against two baseline strategies: static price (where price does not vary across dates) and rule-based pricing (where the price on weekends or during holidays is raised). The baselines were tested by using top-line performance measures including revenue per listing, occupancy rate, and root mean square error (RMSE) across reference and forecast prices. Results proved that the Q-learning agent performed better than both baseline models consistently.

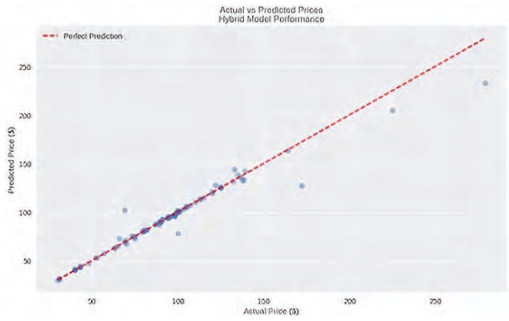

Fig. 3. Actual vs. predicted prices plot

It especially performed well in times of volatile demand, where rule-based and static approaches could not adapt. The learned policy enabled the agent to dynamically change prices according to both internal trends and external competitive trends.

System Integration and Deployment

To provide end users with access to the model outputs, a responsive frontend interface was created with Vite,

Tailwind CSS, and TypeScript. The dashboard presents optimized price recommendations, past trends, and competitor price comparisons. The interface provides hosts with data-driven decision- making capabilities without technical knowledge. For the integration into the backend, the trained Q-learning model was implemented on top of a light-weight Flask API. The API takes user input, i.e., date or listing context, as input and returns the resulting price recommendation. This API-based architecture separates the frontend from model logic, making it easy to scale in the future or integrate with real-time Airbnb data streams.

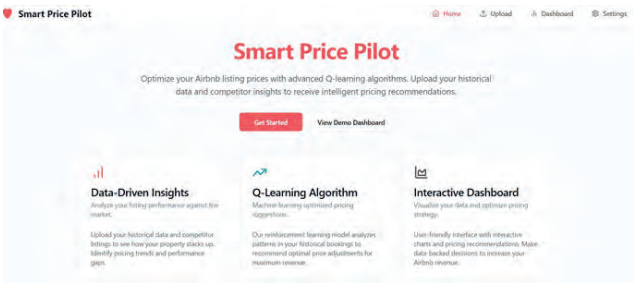

Fig. 4. Smart Price Pilot homepage interface

The entire system (model logic, data pipeline,API, and user interface) was put in place locally for testing and verification. This modular structure makes each component upgradeable independently, resulting in a production-ready solution that is also extensible to more general use cases.

Table 1. Suggested Price vs. Actual Price Based on Q-learning

Sr. No.	Current Price (₹)	Suggested Price (₹)	Change %	Model Action
1	3015	3176	+5.34%	Increase price
2	1500	1689	+12.6%	Increase price
3	4600	4400	-4.35%	Decrease price
4	2210	2250	+1.81%	Slight increase
5	2875	2875	+0.00%	Maintain current

RESULTS

After the model was trained using Q-learning, the results were integrated into a dashboard to make the output easy to understand and usable by Airbnb hosts. The dashboard displayed both the current price of the listing and the price recommended by the model.

Fig. 5. Dashboard with recommended pricing and listing stats

In one of the examples, the current price of the listing was ₹3,015 and the model suggested ₹3,176, which was a 5.34% increase. Similarly, another listing had a current price of ₹1,500 and the model recommended ₹1,689, a 12.6% increase. These differences may seem small, but when considered over a long period and multiple bookings, they can make a significant difference in revenue for the host. The model did not just increase prices arbitrarily; it learned when to raise or reduce prices based on the patterns in the data. In some cases, it lowered the price slightly if the listing was higher than competitor properties in the same area. For example, a listing priced at ₹4,600 was adjusted down to ₹4,400, making it more competitive while still maintaining profitability. In most cases, the model managed to find a balance between maximizing revenue and ensuring that the listing remained attractive to potential guests.

The dashboard also showed a weekly price trend, where the model gave different price suggestions for each day of the week. In general, it suggested higher prices for weekends, especially Friday and Saturday, since these are the days with higher demand. For weekdays like Monday and Tuesday, the prices were slightly lower. This confirmed that the model understood weekly demand patterns and adapted its pricing accordingly.

Another feature of the dashboard was the price comparison section, which showed how the host's property compared to nearby competitor listings in terms of ratings, price, and amenities. This was helpful because it gave the user context for the pricing suggestions. For example, if the host's property had a lower rating or fewer amenities than the competition, the model took that into account while suggesting a price. If the host's property had better ratings or more rooms, the model suggested a slightly higher price to reflect the added value. When users uploaded their data files (including historical data and competitor pricing), the system automatically checked whether all required columns were present.

Fig. 6. Upload interface for historical and competitor data

If there were any errors, it showed a warning and asked the user to fix the file before proceeding. This step made the system more user-friendly and ensured that only clean, usable data was processed.

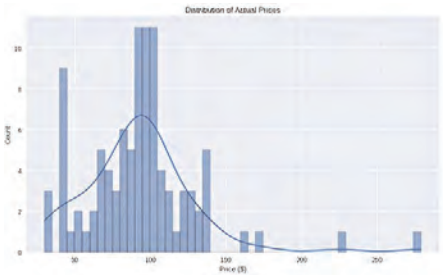

Fig. 7. Market price distribution across listings

Apart from the dashboard, several data visualizations were created during the analysis. These included charts showing the relationship between price and occupancy over time, the distribution of prices across the dataset, and how pricing varied with listing capacity. One graph showed that listings with more bedrooms and higher capacity were generally priced higher, which is expected. Another chart showed that occupancy stayed quite high for many listings, often close to 100%, while prices varied depending on the time of year.

Feature importance was also calculated to understand which factors had the biggest impact on the pricing model. The most important feature turned out to be price_per_ bedroom, followed by the total number of bedrooms and rooms. Other factors like average review rating and number of reviews had some influence but were not as significant. This showed that structural aspects of the listing, like size and capacity, were more important than ratings when it came to deciding price.

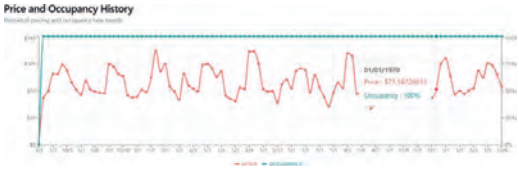

Fig. 8. Trend of price and occupancy over time

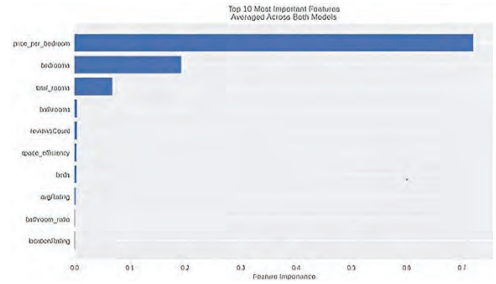

Fig. 9. Top features influencing price prediction

The residual plot confirmed that the model predictions were quite accurate, as most of the residuals were close to zero. This meant that the predicted prices were close to the actual prices and there were no large errors in the system's outputs. The model was able to make consistent predictions across a wide range of listings and scenarios.

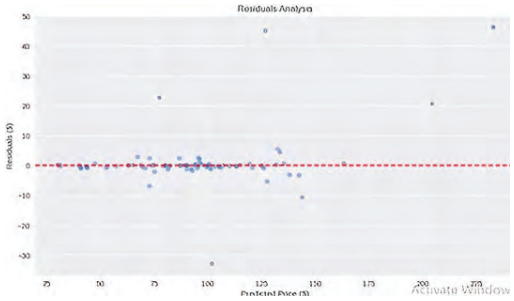

Fig. 10. Residuals of predicted vs. actual prices

Table 2: Day-wise Price Recommendations Based on Q-learning Output

Day	Suggested Price (₹)	Observed Trend
Monday	96	Weekday based rate
Tuesday	96	Stable
Wednesday	97	Slight mid-week rise
Thursday	98	Rising before peak
Friday	115	Peak demand
Saturday	115	Peak demand
Sunday	100	Post-weekend drop

Overall, the results confirmed that the Q-learning model was able to generate meaningful and useful price suggestions that responded to changes in competitor pricing, day of the week, and listing features. The dashboard made it easier for users to understand these results and take action. The system worked smoothly from file upload to price

prediction, and the results matched expectations based on real-world booking behavior. This showed that the model was not only technically sound but also practically useful for Airbnb hosts looking to optimize their pricing and improve their revenue.

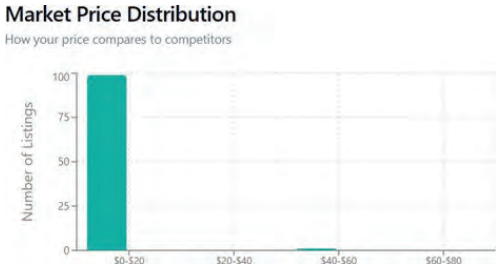

Fig. 11. Distribution of competitor listing prices.

CONCLUSION

Airbnb Price Optimization aimed to overcome the shortcomings of static and rule-based pricing strategies that prevail among Airbnb hosts. By employing Q-learning, we created a dynamic pricing model that could learn from booking results and adapt prices based on a mix of historical information, competitor patterns, and temporal patterns like weekends and holidays. The model was also trained to maximize both revenue and occupancy, balancing the affordability for visitors and profitability for hosts.

Our experiments demonstrated that the Q-learning model surpassed baseline approaches in both revenue generation and responsiveness to shifting market conditions. The application of engineered features such as rolling averages and gap prices from competitors enabled the model to price more sensibly. The reward function was specifically designed to model real-world booking dynamics, prompting the agent to learn pricing policies that are both effective and feasible.

To make the system accessible to non-tech users, we also created a responsive frontend dashboard that displays optimized prices, historical trends, and competition comparisons in an intelligible and interactive manner. This user interface closes the gap between sophisticated machine learning models and day-to-day pricing decisions made by hosts.

Overall, the findings suggest that reinforcement learning, especially Q-learning, can be an effective means of automating pricing in the short-term rental market. With additional development, for example, incorporating real-time data feeds, deployment to production, or host customization capabilities, this system can mature into a useful and implementable solution for dynamic pricing in the hospitality sector.

REFERENCES

1. B. L.G and A. Revathi, "Enhancing Retail Price Optimization Strategies for Improved Performance," Journal of Emerging Technologies and Innovative Research (JETIR), vol. 11, no. 3, Mar. 2024. [Online]. Available: www.jetir.org.
2. L. Di Persio and E. Lalmi, "Maximizing Profitability and Occupancy: An Optimal Pricing Strategy for Airbnb Hosts Using Regression Techniques and Natural Language Processing," Journal of Risk and Financial Management, vol. 17, no. 9, 2024. doi: 10.3390/jrfm17090414.
3. N. Camatti, G. di Tollo, G. Filograsso, and S. Ghilardi, "Predicting Airbnb Pricing: A Comparative Analysis of Artificial Intelligence and Traditional Approaches," Computational Management Science, vol. 21, 2024. [Online]. Available: https://doi.org/10.1007/s10287-024-00511-4.
4. T. Falatouri, F. Darbanian, P. Brandtner, and C. Udokwu, "Predictive Analytics for Demand Forecasting—A Comparison of SARIMA and LSTM in Retail SCM," Procedia Computer Science, vol. 200, pp. 993–1003, 2022. doi: 10.1016/j.procs.2022.10.124.
5. C. Yaiprasert and A. N. Hidayanto, "AI-driven Ensemble Three Machine Learning to Enhance Digital Marketing Strategies in the Food Delivery Business," Intelligent Systems with Applications, vol. 18, 2023. doi: 10.1016/j.iswa.2023.200235.
6. M. Neumüller et al., "Explainable Machine Learning in Retail: Combining Extra Trees Regression and LSTM," Applied Sciences, vol. 13, no. 11112, 2023. doi: 10.3390/app13111112.
7. F. Ferreira, B. Lee, and D. Simchi-Levi, "Analytics for an Online Retailer," Journal of Retailing, vol. 80, no. 3, pp. 261–275, 2019.
8. O. Kulkarni, M. Dahan, and B. Montreuil, "Resilient Hyperconnected Parcel Delivery Network Design Under Disruption Risks," International Journal of Production Economics, vol. 249, Article 108499, 2022. doi: 10.1016/j.ijpe.2022.108499.
9. N. Camatti, G. di Tollo, and R. Pesenti, "Host Type and Pricing on Airbnb: Seasonality and Perceived Market Power," Tourism Management, vol. 88, 2022. doi: 10.1016/j.tourman.2021.104433.
10. C. Adamiak et al., "Current State and Development of Airbnb Accommodation Offer in 167 Countries," Current Issues in Tourism, vol. 25, no. 19, pp. 3131–3149, 2022. doi: 10.1080/13683500.2019.1696758.

Autonomous Decision Making in Supply Chain Leveraging Agentic AI and Blockchain

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ABSTRACT

Modern supply chains face growing complexity and increased in vulnerability due to disruptions, creating an urgent need for intelligent, adaptive and transparent management systems. This study presents an innovative strategy for enhancing the resilience of supply chains by integrating agentic artificial intelligence (AI) with blockchain technology. Within this framework, intelligent AI agents operate independently to evaluate risks, make real-time decisions, and perform operations without relying heavily on human involvement. Blockchain, on other hand is a distributed ledger that keep track of supply chain activities, improving data sharing and trustworthiness in supply chain management process. Agentic AI and Blockchain together have self-learning and automatic decision making capability to manage issue like resource handling and trust between stakeholders involved. The study uses simulation for testing to check efficiency and resilience of AI-blockchain model in complex supply chain.

KEYWORDS *: Supply chain management, Resilience, Agentic artificial intelligence (AI), Blockchain technology.*

INTRODUCTION

Supply chain management is facing issues like data quality, visibility, security, and system integration. Traditional, centralized supply chain systems are heavily dependent on human intervention often struggles to manage these complexities effectively. This over-reliance has become a major barrier to building agile and resilient supply chains. To address this, there is a growing need for decentralized, intelligent systems capable of making autonomous decisions based on real-time data. Agentic Artificial Intelligence (AI) offers a promising solution by enabling real-time decision-making without the constraints of predefined rules or constant human oversight. These intelligent agents can continuously sense and interpret environmental data, allowing the system to detect disruptions early and respond proactively to maintain performance. When combined with blockchain technology, which ensures secure, transparent, and tamper-proof data sharing, the result is a highly resilient supply chain system. This integration not only enhances security and trust but also supports the development of autonomous, self-regulating supply networks better equipped to handle today's dynamic challenges. This study explores how blockchain technology and agentic AI may work together to improve the robustness of contemporary supply chains.

This paper provides an outline for creating resilient and flexible supply chains by fusing AI-driven autonomy with open decentralized data frameworks.

The structure of the paper is as follows: The existing literature is reviewed in Section 2. The research technique is presented in Section 3. The constructed simulation model is described in Section 4. Results and key sights are presented and interpreted in Section 5. Section 6 presents challenges and recommendation for practical implementation. Future study directions are suggested at the end of Section 7.

LITERATURE REVIEW

Supply chain management involves many stakeholders so it is important to have better coordination, faster response times and novel sustainable practices to respond to their growing demands. AI and Blockchain together have the capability to meet these requirements. Agentic AI can make decision on their own with analyzing data in real time. It doesn't require any human intervention, which make them suitable to improve flexibility and smooth collaboration in supply chain management process [1][2].

Conventional AI and Advanced agent concepts find their importance for sustainable practices and collaborative system interaction [3][4]. Organizations able to respond more quickly to unexpected disruptions or changes in market demand by having distributed decision making. [5][6].

Blockchain with decentralized, secure method able to stored unaltered data, building trust among stakeholders, and improving real-time operational visibility [7] [8][9][10]. Several studies show that blockchain implementation positively influences supply chain efficiency and transparency, particularly in logistics and distribution networks [11][12].

When integrated, AI and blockchain create a synergistic platform capable of supporting autonomous operations, real-time analytics, and transparent decision-making. [13][14][15]. Moreover, blockchain plays a pivotal role in ensuring the ethical transparency of AI models, improving stakeholder accountability and governance [16].

Recent work has demonstrated the effectiveness of agentic AI in various supply chain contexts. In retail, AI-powered systems have been shown to improve inventory management, demand forecasting, and customer interaction through automation [17]. In food supply chains, agentic AI enhances decision speed and traceability across complex stakeholder networks , while multi-agent system (MAS) frameworks enable the distributed management of autonomous supply chains [18].

Recent advancements highlight the growing use of technology-driven solutions in areas such as sustainability tracking, carbon emissions monitoring, and automated regulatory compliance particularly in fields like agriculture, logistics, and industrial manufacturing [19], [20], [21].

Integrated systems that combine blockchain, machine learning, and IoT devices are increasingly being developed to make supply chains more intelligent and adaptive. The convergence of blockchain and AI is also gaining traction in other sectors like public institutions to promote policy transparency [22]. The healthcare sector is using it to secure sensitive clinical data [23] and the financial sector is adopting it for decentralized, tamper-proof auditing and reporting processes [24], [25].

Together, these developments point to a broader shift toward intelligent and decentralized systems that enhance operational stability, strengthen data security, and foster open collaboration. The current body of research provides a strong base for advancing frameworks that support secure, autonomous, and sustainability-oriented decision-making within real-world supply chain environments.

METHODOLOGY

Use Case: Food Supply Chain

The research focuses on the food supply chain as a real-world case study due to its high exposure to disruptions like transport delays, supplier breakdowns, and demand fluctuations. Two distinct operational models are constructed for this study:

- Scenario A represents a traditional, centralized food supply chain system. It relies heavily on manual oversight and delayed information flow, making it less responsive to sudden changes or disruptions.
- Scenario B introduces a decentralized framework built upon blockchain technology combined with AI-driven agents. This setup facilitates autonomous operations and instant information exchange across stakeholders without human intervention.

The primary aim is to explore whether the adoption of blockchain and AI together can meaningfully enhance the supply chain's resilience, efficiency, and adaptability in adverse conditions.

System Architecture and Simulation Setup

A simulation environment is created to replicate the functioning of both models under identical disruption conditions. The following design elements are implemented:

- Network Composition: The supply chain is modeled with entities : suppliers, producers, logistics partners, and retailers.
- Autonomous Agents (Scenario B): Each node is equipped with an AI agent capable of making local decisions, forecasting delays, and initiating corrective actions without external input.
- Blockchain Integration: For Scenario B, every transaction and update is recorded on a blockchain ledger to ensure consistency, security, and end-to-end traceability.
- Disruption Simulation: A delay variable is introduced to simulate typical disruptions like late deliveries or supplier downtimes, impacting both scenarios equally.

Performance Indicators and Data Collection

To evaluate system behavior, data is collected from simulation runs based on the following key indicators:

- Operational Cost: Total incurred cost throughout the supply chain during disruption.
- Response Efficiency: Speed at which the system identifies and reacts to disruptions.
- Decision Autonomy: Extent of machine led actions without human commands.
- System Flexibility: The ability to shift plans or reallocate resources during interruptions.
- Information Transparency: Degree of visibility and shared data accuracy across stakeholders.

Each scenario is tested repeatedly to ensure consistency and account for randomness.

Evaluation and Comparative Analysis

Performance data from both scenarios is analyzed quantitatively. A comparative approach is used to measure improvements in resilience and efficiency under stress conditions. Additionally, sensitivity checks are conducted by altering the intensity and frequency of disruptions to understand how each system responds to escalating challenges.

PROPOSED SYSTEM

In the proposed food supply chain system, agentic artificial intelligence (AI) is integrated with blockchain technology to enhance efficiency, resilience, and transparency. As illustrated in Figure 1, specialized AI agents are assigned to gather critical information from various stakeholders across the supply chain. These agents monitor and collect real-time data such as temperature levels, inventory status, delivery schedules, and route conditions. The collected data is securely recorded on a blockchain ledger, which is continuously audited to detect potential disruptions, including product shortages, delivery delays, or regulatory violations. In the event of a disruption such as a prolonged delivery delay smart contracts are automatically triggered. These contracts verify the nature of the disruption and initiate predefined mitigation protocols. The Operational Resilience Score (ORS) is calculated for each scenario, reflects the system's overall ability to respond and adapt to disruptions in real time. The evaluation of system performance was based on five key metrics, each carefully defined and quantified using simulation data.

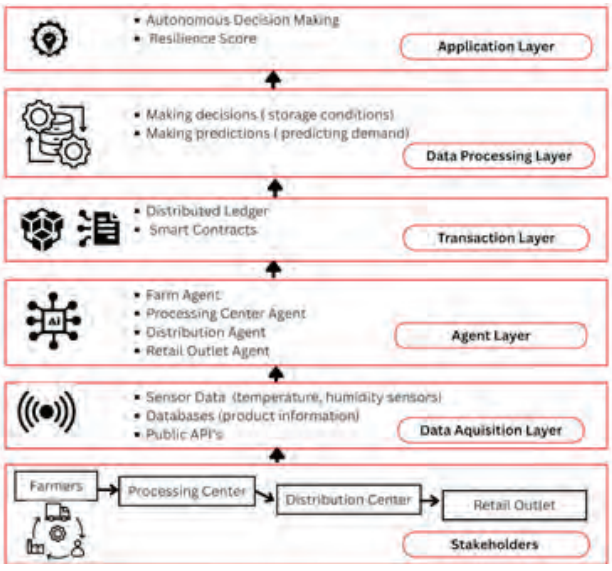

Fig. 1. Proposed Architecture

- Autonomy was assessed by calculating the percentage of decisions independently made by

AI agents without human input. Each decision was securely documented on the blockchain, providing a permanent and verifiable record of autonomous actions.

- Responsiveness was measured by tracking the time taken to detect and respond to disruptions. The use of blockchain's accurate timestamping enabled precise monitoring of response intervals while also enhancing system accountability.
- Transparency reflected the reliability and accessibility of shared information. In the smart supply chain model, this metric showed considerable improvement due to the blockchain's distributed and tamper-resistant ledger, which ensured real-time visibility for all stakeholders.
- Adaptability defined as the system's capacity to dynamically respond to disruptions, by rerouting deliveries or adjusting inventory levels. All such adaptive actions were recorded on the blockchain to support traceability and facilitate continuous optimization.
- Cost efficiency analyzed by examining operational expenses related to maintaining product quality. The blockchain enabled detailed logging of cost-related activities including rerouting, spoilage, and storage allowing for a transparent assessment of efficiency gains.

For consistency and comparative clarity, performance data from multiple simulation runs were averaged and normalized on a scale of 0 to 100 shown in Table 1. This standardized approach ensures reliable comparison across both traditional and smart supply chain scenarios. The methodology adopted is summarized in following steps

Normalize the Metrics

To facilitate a meaningful comparison between the two supply chain models, the raw performance metrics are scaled using min-max normalization (Equation I). This method transforms the values into a standardized range from 0 to 1, based on the minimum and maximum values observed across all scenarios, in Table 2.

$$Xnorm=(X-Xmin)/(Xmax-Xmin) \quad (1)$$

Table 1 : Performance Metrics (Before Normalization)

Metric	Scenario 1	Scenario 2
Autonomy (A)	38	84
Responsiveness (R)	50	92
Transparency (T)	40	96
Adaptability (Ad)	45	90
Cost Efficiency (C)	55	78

Table 2 : Performance Metrics (After Normalization)

Metric	Min	Max	Scenario1 Norm	Scenario2 Norm
Autonomy (A)	38	84	0	1
Responsiveness (R)	50	92	0	1
Transparency (T)	40	96	0	1
Adaptability (Ad)	45	90	0	1
Cost Efficiency (C)	55	78	0	1

Calculate Overall Resilience Score (ORS)

The normalized metrics are combined into a single resilience score by assigning equal weights to each attribute (wi=0.2) and computing the weighted sum using (Equation I).

$$ORS = \sum_{i=1}^{n} wi \times Xnorm \quad (2)$$

RESULT AND DISCUSSION

The simulation results highlight a significant performance difference between the conventional food supply chain and the enhanced with agentic AI and blockchain technologies. The traditional system (Scenario 1) depends on manual processes and centralized control, Scenario 2 leverages autonomous agents and blockchain-enabled data sharing (figure 2). The comparison show The conventional model (Scenario 1), which relies on manual coordination and centralized systems, shows limitations in agility, transparency, and disruption response.

On the other hand, Scenario 2 introduces decentralized decision-making through AI agents and secure, real-time data sharing via blockchain. This setup leads to stronger performance across multiple areas: Autonomy, Responsiveness, Transparency, Adaptability, Cost Efficiency shown in figure 3.

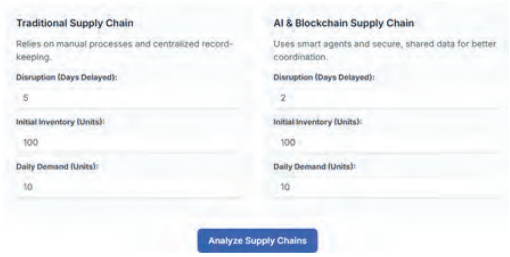

Fig 2. Traditional vs. AI/Blockchain Supply Chain Analysis

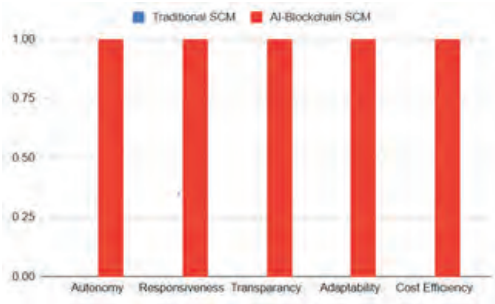

Fig. 3 Metric Comparison of Traditional

System with AI & Blockchain

Overall Resilience Score (ORS) of scenario 2 found as 1, while Scenario 1 scored 0 (figure 4). These results clearly demonstrate how each supply chain model responds to disruption.

Fig. 4. Resilience Score

The ORS quantifies the system's capacity to maintain operational performance. The ORS scores obtained in both the scenario indicates that integrating intelligent, decentralized technologies can greatly enhance the resilience of food supply chains, especially when managing time-sensitive or perishable products. To validate the effectiveness of the improved model, each result was compared against conventional model.

The outcomes demonstrated significant improvements across key performance indicators as shown in figure 5. Order Fulfilment Rate improved, exceeding 98% in Scenario 2 compared to 86% in Scenario 1, indicating enhanced responsiveness and service reliability. Lead Time Fluctuation was reduced by 60% as a result of streamlined, automated workflows that minimized .

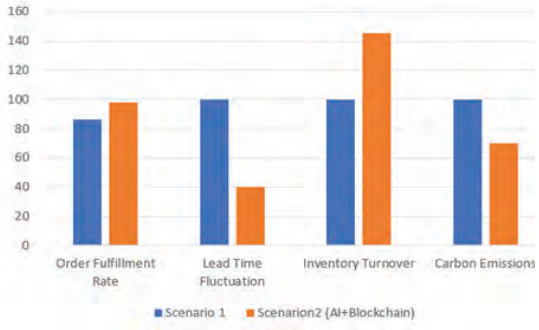

Fig. 5. Comparing Conventional Model with Proposed Model

process delays and uncertainties. Inventory Turnover increased by 45%, highlighting the effectiveness of AI-driven demand forecasting and agile restocking mechanisms. Furthermore, Carbon Emissions were lowered due to optimized logistics operations and the reduction of excess inventory, supporting both sustainability and efficiency objectives. These results collectively confirm that the integration of intelligent technologies can significantly enhance overall supply chain performance.

Simulations show promising outcomes for the integration of agentic AI and blockchain within food supply chains, actual implementation in real environments introduces a set of complexities, multidimensional challenges. These challenges are related not only to technology, but also to organizational readiness and regulatory frameworks.

Challenges and Practical Recommendations

Key Implementation Challenges

- Data Inconsistency Across Participants:

Food supply chains often involve a diverse group of stakeholders including producers, distributors, and retailers each using different information systems. Without uniform data standards, AI agents may struggle to process and respond to inconsistent formats, creating barriers to seamless automation and communication.

- Infrastructure Gaps and Budgetary Constraints:

Deploying AI and blockchain technologies typically requires investment in digital infrastructure, skilled

personnel, and ongoing system maintenance. This can be a significant obstacle for smaller players, such as rural suppliers or independent grocers, who may lack the financial and technical resources necessary to participate effectively.

- Scepticism Toward AI-Driven Operations:

Entrusting AI agents with critical decisions can raise concerns among stakeholders, especially in highly regulated environments like food safety. If AI decisions are not transparent or explainable, stakeholders may resist their adoption, fearing errors, liability, or loss of control.

- Scalability and Latency Issues:

As the system scales to include more nodes and data streams from IoT sensors, AI processors, and blockchain transactions network congestion and response delays can emerge. Without performance-optimized architecture, such issues can hinder the system's ability to operate in real time, especially under peak loads.

- Legal and Policy Uncertainty:

The legal recognition of smart contracts and AI-based decision-making varies across regions. In the absence of clear legal guidelines or frameworks, especially in cross-border supply chain operations, organizations may face challenges in compliance, enforceability, and liability management.

Recommendations for Practical Implementation

- Initiate with Scalable Pilot Projects:

Organizations should begin by deploying modular systems in targeted area such as cold chain tracking or inventory alerts before expanding to full-scale integration. This phased approach helps identify operational risks early and refine system performance.

- Leverage Permissioned Blockchain Models:

Using private or consortium-based blockchain networks can enhance data governance. By restricting access to verified participants, such models protect sensitive information while maintaining transparency within authorized boundaries.

- Promote Interoperability Through Common Standards

Collaboratively developing standardized data formats and communication protocols among stakeholders will help improve system compatibility, ease integration, and reduce data misinterpretation.

- Build Adaptive Smart Contracts:

Smart contracts should incorporate adjustable rule sets that account for real-world variability. These should include conditions for exceptions, fallback actions, and human overrides, enhancing resilience in unpredictable scenarios.

- Integrate Ethical and Sustainability Objectives:

Beyond operational efficiency, AI logic should be programmed with ethical and environmental priorities such as minimizing spoilage, reducing energy consumption, and supporting sustainable sourcing. This ensures the technology aligns with broader social and ecological goals.

By acknowledging these challenges early and adopting a thoughtful, phased deployment strategy, stakeholders can ensure that the integration of agentic AI and blockchain into supply chains is practical, inclusive, and aligned with industry regulations and sustainability commitments.

CONCLUSION

In today's unpredictable global environment, supply chains need more than just automation; they require systems that can think, adapt, and act on their own. This paper explored how agentic AI, which can make independent decisions based on changing conditions, offers a powerful way to meet these demands. AI and Blockchain provides proactive approach of identifying potential risks early, respond quickly, and keep operations running smoothly rather than reacting to problems after they occur which improves trust, transparency and data sharing. Intelligent AI agents with secure, decentralized data systems creates a model for resilient supply chains. In the future, there is significant potential to expand on these concepts by collaborating various AI agents to increase the system's responsiveness. Explainable AI would also be included to improve trust and accountability. In blockchain, interoperable concept needs to explore as it could make international supply chain operations faster and more efficient. As technology evolves, bringing in tools like digital twins could take things to the next level.

REFERENCES

1. Kalisetty, S. (2024). Agentic AI and predictive analytics: Revolutionizing retail supply chain management for next-gen resilience and efficiency. American Data Science Journal of Advanced Computing, 2(1).
2. Aylak, B. L. (2025). SustAI-SCM: Intelligent supply chain process automation with agentic AI for sustainability and cost efficiency. Sustainability, 17(6), 2453.
3. Hughes, L., et al. (2025). AI agents and agentic systems: A multi-expert analysis. Journal of Computer Information Systems, 1–29.
4. Sapkota, R., Roumeliotis, K. I., & Karkee, M. (2025). AI agents vs. agentic AI: A conceptual taxonomy, applications and challenge. arXiv preprint, arXiv:2505.10468.
5. Pamisetty, A. (2024). Application of agentic artificial intelligence in autonomous decision making across food supply chains. European Data Science Journal, 1(1).
6. Kalisetty, S., & Singireddy, J. (2023). Agentic AI in retail – A paradigm shift in autonomous customer interaction and supply chain automation. American Advanced Journal of Emerging Disciplines, 1(1).
7. Oriekhoe, O. I., et al. (2024). Blockchain in supply chain management: A review of efficiency, transparency, and innovation. International Journal of Scientific Research Archives, 11(1), 173–181.
8. Sharabati, A. A. A., & Jreisat, E. R. (2024). Blockchain technology implementation in supply chain management: A literature review. Sustainability, 16(7), 2823.
9. Raja, J., et al. (2025). Blockchain technology in supply chain management enhancing transparency and efficiency. In ITM Web of Conferences, 76, 02011.
10. Dudczyk, P., Dunston, J. K., & Crosby, G. V. (2024). Blockchain technology for global supply chain management: A survey applications, challenges, opportunities and implications. IEEE Access, 12, 70065–70088.
11. Alkatheeri, H., & Ahmad, S. Z. (2024). Examining blockchain adoption determinants and supply chain performance: An empirical study in the logistics and supply chain management industry. Journal of Modeling in Management, 19(5), 1566–1591.
12. Tsolakis, N., et al. (2023). Artificial intelligence and blockchain implementation in supply chains: A pathway to sustainability and data monetisation. Annals of Operations Research, 327, 157–210.
13. Karim, M. M., et al. (2025). AI agents meet blockchain: A survey on secure and scalable collaboration for multi-agents. Future Internet, 17(2), 57.
14. Zuo, Y. (2024). Exploring the synergy: AI enhancing blockchain, blockchain empowering AI, and their convergence across IoT applications and beyond. IEEE Internet of Things Journal.
15. Li, J., et al. (2024). Blockchain intelligence: Intelligent blockchains for web 3.0 and beyond. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 54(11), 6633–6642.
16. Akther, A., et al. (2025). Blockchain as a platform for artificial intelligence (AI) transparency. arXiv preprint, arXiv:2503.08699.
17. Yu, E., et al. (2024). Blockchain-based AI agent and autonomous world infrastructure. In 2024 IEEE Conference on Artificial Intelligence (CAI) (pp. 278–283). IEEE.
18. Xu, L., Mak, S., Minaricova, M., & Brintrup, A. (2024). On implementing autonomous supply chains: A multi-agent system approach. Computers in Industry, 161, 104120.
19. Alshurideh, M. T., et al. (2024). Empowering supply chain management system with machine learning and blockchain technology. In Cyber Security Impact on Digitalization and Business Intelligence (pp. 335–349). Springer.
20. Patro, P. K., et al. (2024). Blockchain, IoT, and AI-based framework for traceability in carbon capture utilization storage (CCUS) supply chain. In Proceedings of the 6th Blockchain and Internet of Things Conference (pp. 67–73).
21. Zawish, M., et al. (2022). Toward on-device AI and blockchain for 6G-enabled agricultural supply chain management. IEEE Internet of Things Magazine, 5(2), 160–166.
22. Jayanthi, S., et al. (2024). An explorative study of explainable AI and blockchain integration in public administration. In Applications of Blockchain and Artificial Intelligence in Finance and Governance (pp. 230–271). CRC Press.
23. Leiva, V., & Castro, C. (2025). Artificial intelligence and blockchain in clinical trials: Enhancing data governance efficiency, integrity, and transparency. Bioanalysis, 17(3), 161–176.
24. Agrawal, D., et al. (2025). Blockchain and AI integration for transparent and secured financial record keeping. In Recent Trends in Engineering and Science for Resource Optimization and Sustainable Development (pp. 72–76).
25. Han, H., et al. (2023). Accounting and auditing with blockchain technology and artificial intelligence: A literature review. International Journal of Accounting Information Systems, 48, 100598.

Robust Deepfake Detection: A Multi-Layered Approach Combining Spatial and Temporal Analysis

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ABSTRACT

A Deepfake Detection System with deep learning capabilities and artificial intelligence precision performs detection of manipulated content according to this paper. The system analyzes motion errors and lighting anomalies and facial characteristics by applying deep learning transformers and Convolutional Neural Networks (CNNs) technique. The detection's resilience can be improved by implementing frequency-domain approaches together with forensic examination. The model gains the ability to detect various deepfake production methods by undergoing training with multiple dataset types. HyperGAN demonstrates leading performance capabilities according to experimental findings in its ability to discern between authentic and fraudulent content. This method ensures content validity which allows its application in cybersecurity and journalism as well as social media. Digital media protection against deepfake malicious use becomes possible through this detection method which delivers trustworthy and scalable detection capabilities to establish confidence in online information sharing.

KEYWORDS *: Deepfake detection, Deep learning, Artificial intelligence, Anomalies, Convolutional neural networks (CNNs), Transformer-based models, Motion abnormalities, Lighting irregularities, Facial traits, Frequency-domain analysis, Forensic analysis, Cybersecurity, Digital media protection, Misinformation prevention.*

INTRODUCTION

With the rapid advancements in artificial intelligence (AI) and deep learning technology, 'Deepfake' is emerging as a threat to digital security, media integrity, and public trust. With the help of Generative Adversarial Network (GANs) [2] and artificial intelligence techniques deepfake videos and images have become so distorted that specialists currently experience significant difficulty in detecting them. The deepfake detection methods which are used today use conventional techniques that require handcrafted features and supervised learning models while needing extensive labeled data although they face difficulties generalizing new deepfake types because biased datacontinues to exist. [3] [7]. Our focus behind the Deepfake Detection project remains on detecting together with resolving the potential risks and ethical matters that emerge from deepfake technology abuse.

Deepfakes represent artificial media that emerge from applying deep learning techniques in computer science productions. They generate realistic look-alikes from audiovisual assets while maintaining deceptive contents within them. The quick advancement of deepfake technology production makes the separation of original from modified content increasingly problematic for detecting falsified media. [5]. This is raising high concerns regarding misinformation, privacy violations, security threats, defamation, fraud, and other malicious activities [14]. It is crucial to detect and mitigate the impacts of deepfakes to maintain individuals' trust in digital media and protect organizations from security concerns [3] [6]. The aim of our project is to develop effective methods and tools for identifying deepfakes with high accuracy at a low cost model. This involves creating or improving algorithms and systems that can analyze digital content to determine its authenticity [7]. The goal is to enable users, platforms, and authorities

to detect manipulated media and respond appropriately to prevent the spread of false or harmful content. The specific objectives of our deepfake detection project includes:

- Development of Detection Algorithms: Create or enhance algorithms that can reliably detect deepfakes using various techniques, such as machine learning models like LSTM and ResNext.
- Near-real-Time Detection: Developing system capable of detecting deepfakes in near-real-time, which is crucial for applications like live video by recording it. streaming.
- User Accessibility: Create user-friendly interfaces and tools that make it easier for individuals and organizations to deploy and utilize deepfake detection solutions.

The detection of deepfakes relies on the combination of frequency analysis together with deep learning models which include EfficientNet and Vision Transformers and CNNs but struggle against evolving deepfake techniques [4]. The detection system conducts anomaly identification by performing pixel-to-frame analysis after extracting key frames with AI support involved in identification. A reliable system can achieve better results through evaluating facial expressions and textures as well as frequency artifacts. A multi-faceted approach is crucial [14]. The initiative builds digital media authenticity standards under the condition of real-time detection systems and robustness against adversarial threats and minimal computational requirements for resource constrained implementations [12] [7] [15].

Research Questions and How to Address Them

1) Data Preprocessing and Feature Extraction: We are analyzing both spatial and temporal features in images and videos, extracting statistical and frequency-based characteristics that highlight deepfake anomalies.
2) Anomaly Detection Model Training: We utilize unsupervised and semi-supervised machine learning models, such as Long Short-Term Memory (LSTM) networks and ResNeXt, to learn normal distributions and detect deviations which indicates deepfakes.
3) Evaluation and Benchmarking: Our proposed method is tested on standard deepfake datasets, and its performance is compared with existing cutting-edge detection techniques in terms of accuracy, precision, recall, and robustness.
4) Generalization Analysis: We examine the model's ability to detect deepfakes from novel architectures, ensuring its effectiveness against the evolving attack strategies.

These research areas aim to enhance the effectiveness and accessibility of ML-based Deepfake Detection system. Through this study, we aim to contribute to the development of more resilient and adaptable deepfake detection system, which addresses the growing concerns surrounding AI-generated media manipulation.

LITERATURE ANALYSIS

Various researchers have explored different detection methods to counteract the increasing realism of AI-generated synthetic media. This section provides an overview of some existing research, highlighting their methodologies, their effectiveness, and the challenges associated with those deepfake detection systems.

The work introduced in [8] the new Deepfake framework based on physiological measurements is done with the help of remote photoplethysmography (RPPG), information about heart rate. The RPPG method analyzes video sequences looking for subtle color changes in human skin where human blood is present under tissue. This task examines the extent to which RPPGs can help detect deep-fark videos. The proposed fake detector, named Deepfakes on-Phys, extracts spatial and temporal information from video frames and is extracted to analyze and combine both sources to better detect fake videos. The audio-video deepfake dataset, research at Fakeavceleb in [1], includes not only video but also the respective synthesized lip-synchronized fake audio. The most common generation method has been created for data records. They have selected YouTube videos from celebrities from four ethnic backgrounds to develop realistic multimodal datasets that deal with racist distortions and further develop the development of multimodal deep detectors. They evaluated Deepfake Data Record and conducted several experiments using the latest and most recent technology identification

methods to demonstrate the challenges and usefulness of detailed data in multimodal audio video.

In this paper [9], a foldable-LSTM-based residual network was developed. This shoots time information from the video as input and input to help identify unnatural artifacts present between frames of a Deepfake video. They proposed a transfer based approach to generalizing various deep-fark methods. Strict experiments using datasets using Faceforensics++ have shown that previously proposed methods of recognition methods for in-site recognition methods outweigh the generalizations of various deeper methods when it is better to generalize them.

This paper from [10] shows an automatic and efficient way to detect facial operations in video. Traditional imaging forensic technology is usually not well suited to for video because of significant data damage. Therefore, this work follows a deep learning approach and presents two networks. These high-speed networks evaluate both existing data records and data records created from online videos. This test shows a highly successful identification rate of over 98 percentage on Deepake and over 95 percentage on Face to face.

The work in [11] deals with the problem of face manipulation detection in video sequences aimed at modern face manipulation. In particular, it examines an ensemble of various trained folding models of neural networks (CNNs). In the proposed solution, various models from the basic network (i.e., EfficientNetB4) are obtained from two different concepts. (i) Caution level. (ii) Siamese training. The combination of these networks has been shown to lead to recognition results in two published data records with over 119,000 videos. The work in [12] advocates robust training for improving the generalization ability. It believes training with samples that are adversarially crafted to attack the classification models, improves the generalization ability considerably. Considering that AI-based face manipulation often leads to high-frequency artifacts that can be easily spotted (by models) yet difficult to generalize, it further proposes a new adversarial training method that attempts to blur out these artifacts, by introducing pixel-wise Gaussian blurring. Plenty of empirical evidence show that, with adversarial training, models are forced to learn more discriminative and generalizable features.

Research Gaps

1) Difficulty in detecting physiological signals on missing pulse signals.
2) Datasets focusing on video or audios only of celebrities.
3) Limitations, if facts associated for checking claims are not present.
4) Struggles with high resolution deepfakes.
5) Struggles with generalization to unseen deepfake techniques.
6) Limited use of lightweight or real-time models for deployment.
7) Over-reliance on Benchmark Datasets.

METHODOLOGY

A system uses AI detection to spot unnatural expressions and gestures and eye blink behavior which provide signs of deepfake generation while the technology analyzes improper lip-sync coordination between voice and movement. Among its features AI analyzes inconsistent objects like eye shadows while monitoring environment elements and eye areas and checks background changes as signs of deepfake alteration through audio assessments of additional noises. This system conducts thorough checks of background objects for subtle signs of deepfake tampering. Several persons can help expose deepfake content through multiple recognition methods.

System Architecture

Layer 1: Colorimetric and Tonal Anomaly Detection Deepfake videos often reveal subtle but detectable irregularities in lighting, shading, and color that stem from the generative models' limited understanding of how light interacts with real-world textures and surfaces. Even when a fake appears visually authentic, it may carry imperceptible pixel-level anomalies that suggest synthetic manipulation. To uncover these clues, a pre-trained ResNet-18 convolutional neural network is employed. The operational pipeline of the system follows the stages illustrated in Fig. 1 while maintaining rigorous definitions:

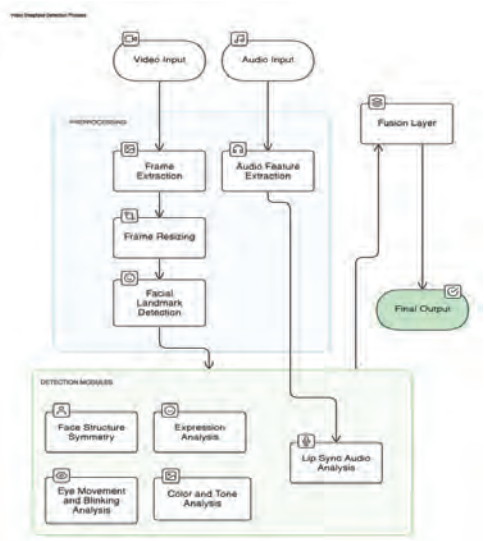

Fig. 1. System Architecture

1) Data Acquisition and Preparation: The system processes digital video data from both authentic and synthetic sources, supporting various video formats, resolutions, and encoding methods. The video is divided into frames through time-based segmentation, with the frame quantity (N) serving as a key hyperparameter. Our research finds N=10 to be optimal for deepfake detection in practical applications.

2) Pre-processing and Feature Engineering: Preprocessing operations standardize data by minimizing environmental impacts and focusing on key facial regions. Facial landmarks are detected using the Mediapipe framework [7], allowing for precise measurements like eye aspect ratio and lip distance. After landmark detection, an affine transformation normalizes facial poses, and the cropped facial regions are resized to 224x224 pixels to ensure consistency with pre-trained CNN models.

3) Dataset Partitioning and Management: The dataset, consisting of normalized facial images and MFCC feature vectors, is divided into three subsets: the Training Set for model learning, the Validation Set for hyperparameter tuning, and the Testing Set for independent evaluation. This partitioning ensures unbiased model evaluation and generalization to new data.

4) Five Layer Extraction & Analysis: The system's core functionality is powered by five analysis layers that focus on feature extraction and classification. These layers process video and audio data independently, generating probability scores for each frame to indicate the likelihood of deepfake manipulation.

5) Fusion Layer: The Fusion Layer consolidates the probability scores from the five analysis layers (color, blink, expression, lipsync, and symmetry) to produce the final deepfake classification result. This layer employs logistic regression to combine the probabilistic outputs, with each score weighted based on its importance in the decisionmaking process. The logistic regression model performs a weighted sum of the input probabilities, followed by a sigmoid transformation to output a final probability score Pfinal between 0 and 1, indicating the likelihood of the video being a deepfake.The fusion process enables the system to account for various feature modalities and enhances classification accuracy by adapting the contribution of each analysis layer through learned weights, ensuring optimal performance in deepfake detection.

PROPOSED SYSTEM

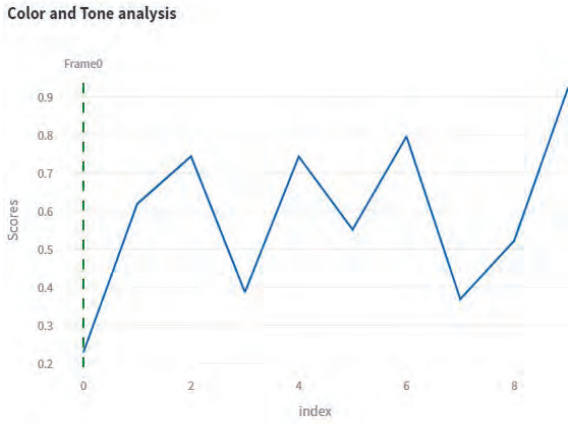

Fig. 2. Color and Tone Analysis

The proposed system consists of five layers that will analyze the media given to the deepfake detection system that will detect if it is manipulated data or not. Layer 1: Colorimetric and Tonal Anomaly Detection Deepfake videos often reveal subtle but detectable irregularities in lighting, shading, and color that stem

from the generative models' limited understanding of how light interacts with real-world textures and surfaces. Even when a fake appears visually authentic, it may carry imperceptible pixel-level anomalies that suggest synthetic manipulation. To uncover these clues, a pre-trained ResNet-18 convolutional neural network is employed.

This model, known for its strength in extracting both lowlevel and high-level features, is fine-tune specifically for identifying signs of tonal and colorimetric inconsistencies between real and fake facial imagery as shown in Fig. 2. It processes RGB video frames of facial regions and returns a probability score indicating whether the lighting, shading, or color patterns deviate from those typically observed in genuine content.

The residual connections within ResNet-18 allow it to retain and combine information from various depths of the network, making it highly sensitive to subtle transitions in tone or light. This capability enables it to detect artifacts like inconsistent shadows, overly smooth skin textures, or implausible lighting gradients—all signs that point toward generative synthesis.

Layer 2: Oculomotor and Palpebral Dynamics Analysis Oculomotor (gaze) and palpebral (blink) behaviors follow natural temporal and statistical patterns that deepfakes often fail to replicate accurately. Irregular blinking or uncoordinated eye movements can indicate facial manipulation. To detect such anomalies, the model uses a two-layer LSTM network with 64 hidden units per layer. LSTMs are ideal for processing sequential data and capturing long-term temporal dependencies, making them effective for modeling natural eye movement patterns. The input to the LSTM is a sequence of Eye Aspect Ratio (EAR) values, a scalar metric representing eyelid openness. EAR is calculated from seven facial landmarks near the eyes, extracted using the Mediapipe framework. The formula is:

EAR = (p2 - p6 + p3 - p5) / (2 * p1 - p4)

EAR values are computed for both eyes in each frame, averaged, and passed into the LSTM. The network processes these sequentially, using its internal memory to learn natural blinking patterns and detect deviations.

The final output passes through a fully connected layer and a sigmoid activation, producing a probability score (0–1) indicating the likelihood of manipulation. Higher scores suggest abnormal blinking or eye motion consistent with deepfakes.

Layer 3: Facial Expression Consistency Evaluation Deepfake techniques occasionally produce expression inconsistencies that appear between successive frames as well as between audio and visual content and overall video context information. The generative models face limitations when reproducing human facial expression dynamics because these expressions represent complex behavioral patterns. The detection of inconsistent elements serves as an important sign to identify content alterations. The multilayer perception section of this layer uses the pre-trained DeepFace model [9] as its base. The extensive training of DeepFace on facial images enables it to deliver superior accuracy when detecting basic along with subtle facial expressions. Implementing a pre-trained model eliminates the requirement for scattering training from the beginning on expression data which results in substantial cost and time savings for development processes.

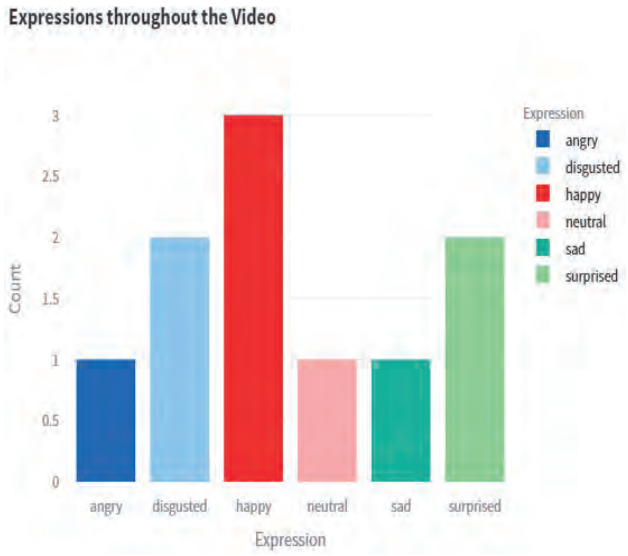

Fig. 3. Expressions Consistency Evaluation

As shown in Fig. 3, a single pre-processed video frame serves as the input data for this layer after it undergoes cropping and normalization as well as resizing.

The final output constitutes probability values between 0 and 1 that describe the likelihood of manipulation. The DeepFace model handles input frames one by one to assess facial spatial structure for emotion inference.

The system determines whether the facial expression belongs to the real category or represents a fake expression.

Layer 4: Audiovisual Synchronization Analysis Lip movements and vocal articulation are closely coupled in human speech. Slight mismatches between the movement of the mouth and the accompanying audio can be jarring and often arise in deepfakes that attempt to re-dub speech or reconstruct facial motion post-hoc. Even when visual alignment appears acceptable at first glance, precise synchronization remains difficult for generative models to replicate at a granular level.

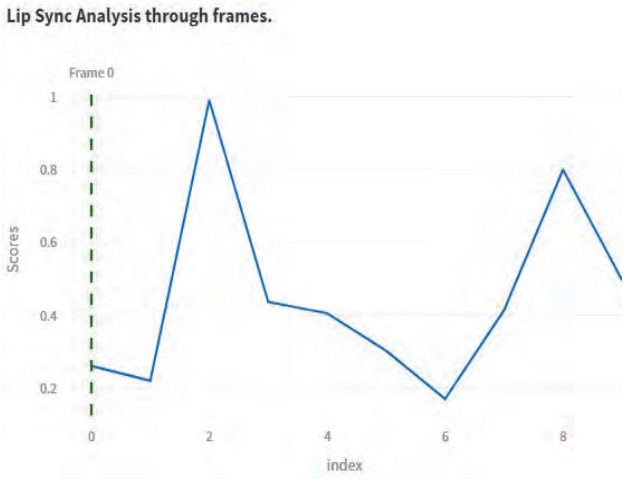

Fig. 4. Audio-Visual Analysis

As shows in Fig. 4, to detect these mismatches, an LSTM model is used to jointly analyze features extracted from both the video and its audio stream. From the video, it processes measurements of mouth shape and openness over time, while from the audio, it extracts spectral features such as Mel-frequency cepstral coefficients (MFCCs) that characterize speech phonemes. The model then analyzes whether these two sequences align properly in terms of timing and shape dynamics. If a vowel or consonant is heard but not properly reflected in lip shape—or if there is a time lag between spoken words and corresponding movements—the model assigns a higher probability that the video has been manipulated. These minor misalignments often escape human detection, but they are strong indicators of synthetic synthesis.

Layer 5: Facial Symmetry Anomaly Detection Human faces show important symmetrical patterns when measured by vertical axes although true symmetry does not exist fully in natural faces. Both parts of the face normally display mirror-like correspondence between each other. During deepfake synthesis when blending or warping multiple facial regions occurs the process results in asymmetries which deviate from authentic subjects' facial symmetry statistical distribution patterns. The identification of asymmetrical patterns in vertically symmetrical facial areas constitutes a beneficial indicator for confirming manipulated content. The model run uses a proprietary CNN architecture which functions at this stage. The network architecture of CNN was designed to identify features which detect minor irregularities in bilateral symmetry patterns in facial images. A custom CNN architecture contains these main parts: Convolutional Layers: Two convolutional layers with an increasing number of filters. Two convolutional layers exist in YOLO where the first layer uses 16 filters before the second layer enhances the number of filters to 32. The two convolutional layers learn spatially localized features that represent facial structure in addition to facial symmetry. The convolutional kernels moving across input images perform dot product computations on image areas of 3x3 dimensions in each sliding step. The network benefits from learning multiple types of features through its multiple filter system. The addition of same padding produces consistent dimensions of feature maps following convolution operations.

Each convolutional layer gets a max-pooling layer as an immediate succession. Max-pooling performs spatial resolution reduction through an operation that downsampled the feature maps by applying a 2x2 window with a stride of 2. The downsampling operation benefits the subsequent layers by reducing computational expense and demonstrates translation invariance and helps prevent overfitting through parameter reduction.

The Feature Mapping occurs throughout two fully connected (dense) layers which translate extracted features from convolutional and pooling layers into one single output value. Both the first fully connected layer contains 128 units and the second (output) layer includes only one unit. What the full-connected layers do is perform a non-linear operation on the extracted features which reveals elaborate connections between those features and facial asymmetry.

The Rectified Linear Unit (ReLU) activation functions serve between convolutional layers together with the first fully connected layer in this model. The ReLU activation function brings model non-linearity so the system can detect complex nonlinear patterns in the data between features and predictions. The ReLU function reaches its maximum value at zero while keeping all values above zero.

The sigmoid activation function produces the last output layer of the CNN. The output of the final fully connected layer transforms to a probability score between 0 and 1 by using the sigmoid function which indicates the chance of abnormal facial asymmetry. Here the REsNET layer receives as input previously processed video frames and their associated facial landmarks that have been detected by Mediapipe.

The output layer generates an output value between 0 and 1 which represents the potential level of deepfake manipulation through facial asymmetry according to the custom CNN analysis. The magnitude of the probability score determines how likely manipulation is to have occurred.

Training the custom CNN uses facial landmarks as the direct source but during inference these landmarks become inaccessible to the network. The image is the input. Through training with landmark information as part of ground truth the CNN learned to identify image features which show symmetry or asymmetry characteristics. During training the data pairs should contain (image, symmetry label) where the symmetry label originates from landmark examination.

RESULT AND DISCUSSION

The below image Fig. 5 shows the working of the model. In this, the model has extracted specific frames from the video to analyze. Frames 1, 2, and 3 show the same person in a consistent pose, but there may be subtle deepfake artifacts.

Frame 4 shows a noticeable distortion (unnatural face proportion or texture), which is a common sign of deepfake manipulation. Frame 5 appears normal but is likely classified based on the model's assessment of deepfake cues.1 out of 8 frames is identified as real and 7 out of 8 frames are identified as deepfake therefore 87.5% frames are fake and 12.5% frames are real.

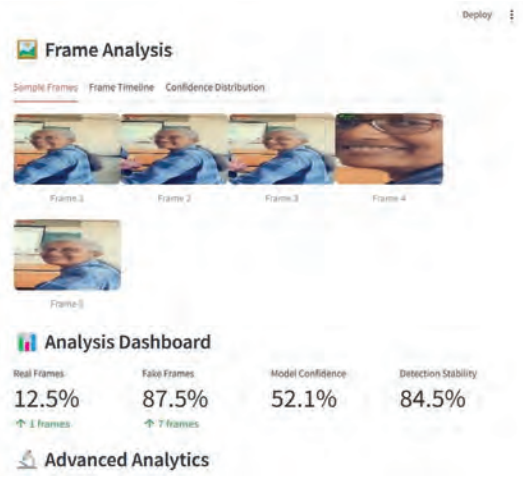

Fig. 5. Deepfake Detecting Model

As showm in Fig. 6, a model's confidence metric indicates how sure the model is about its classification decisions. A confidence of 52.1% is relatively low, suggesting that the fake-real classification is somewhat uncertain.

Fig. 6 Confidence metrics over frames

An 84.5% detection stability means the model's predictions are relatively steady across the video, which implies the deepfake signs are persistent rather than sporadic. This deepfake detection model has flagged the majority of frames as manipulated, indicating a high likelihood that this video is AI-generated or altered.

In Fig. 7, the output analyzed is shown whether it is real or fake of the chosen media. The analysis reveals media metadata such as 7.66-second runtime with 30 frames per second and 230 total frames and shows 8 frames

were analyzed. Additionally, it presents analysis metrics which demonstrate 0.084 confidence volatility and 0.750 frame consistency and displays a deepfake probability gauge reporting high suspicion of manipulation. The evaluation concludes with a FAKE classification of the video content.

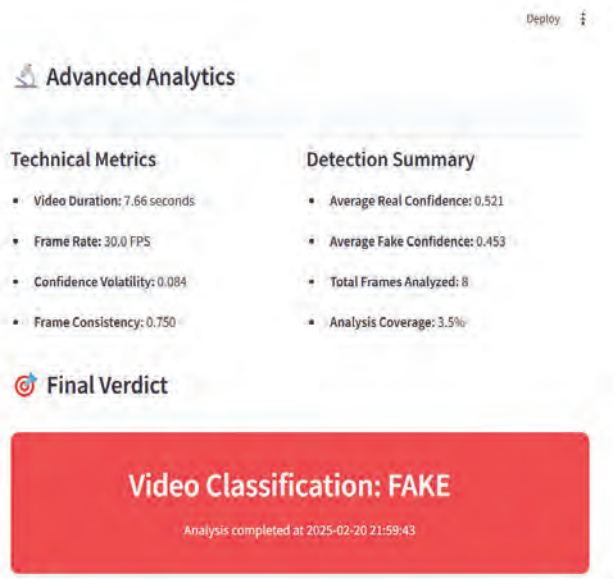

Fig. 7 Analyzed Output

The deepfake detection model follows a structured pipeline consisting of pre-processing, feature extraction, and classification. The pre-processing stage includes video-to-frame conversion, face detection, and face cropping, ensuring that the model focuses on relevant facial features. The dataset is then split into training and testing subsets before passing through the deepfake detection model. The deepfake detection model utilizes ResNext feature extraction and LSTM-based classification to distinguish between real and fake frames. The detection results show a strong ability to identify deepfake frames but also indicate a need for improvement in model confidence. The deepfake detection model was also tested and the results are displayed in Fig 7. The model analyzed individual frames and classified them as either real or fake using a deep learning-based detection approach.

CONCLUSION

In conclusion, the proposed multi-layered deepfake detection system presents a comprehensive and robust framework for identifying synthetic media by leveraging both spatial and temporal inconsistencies across various facets of facial behavior and audiovisual alignment. By integrating specialized models—including ResNet-18 for pixel-level colorimetric analysis, LSTMs for temporal modeling of eye dynamics and lip synchronization, DeepFace for emotional congruence assessment, and a custom CNN for facial symmetry evaluation—the system effectively captures a wide range of manipulation artifacts that often elude human perception. The fusion layer consolidates these heterogeneous signals through a logistic regression model, ensuring that the final classification benefits from the complementary strengths of each detection pathway. This modular architecture not only enhances detection accuracy but also allows for scalability and future integration of additional behavioral or physical cues, such as microexpression tracking or physiological signal analysis. Thorough training and evaluation on diverse datasets ensure the system's generalizability to real-world scenarios, while the deployment pipeline is optimized for low-latency inference, making it suitable for real-time applications including live surveillance, media verification, and social platform moderation. Overall, the system offers a technically sound, data-driven approach to combatting the growing threat of deepfakes, contributing significantly to the reliability, security, and trustworthiness of digital media.

REFERENCES

1. Hasam Khalid, Shahroz Tariq, Minha Kim, Simon S. Woo, "FakeAVCeleb: A Novel Audio-Video Multimodal Deepfake Dataset," arXiv preprint arXiv:2108.05080, Aug. 2021. Accessed on: Jun. 27, 2025. \[Online]. Available: https://arxiv.org/pdf/2108.05080
2. Hasam Khalid, Shahroz Tariq, Minha Kim, Simon S. Woo, "FakeAVCeleb: A Novel Audio-Video Multimodal Deepfake Dataset," arXiv preprint arXiv:2108.05080, Aug. 2021. Accessed on: Jun. 27, 2025. \[Online]. Available: https://arxiv.org/pdf/2108.05080
3. Mohamed R. Shoaib, Zefan Wang, Milad Taleby Ahvanooey, Jun Zhao, "Deepfakes, Misinformation, and Disinformation in the Era of Frontier AI, Generative AI, and Large AI Models," arXiv preprint arXiv:2311.17394, Nov. 2023. Accessed on: Jun. 27, 2025. \[Online]. Available: https://arxiv.org/abs/2311.17394

4. Davide Coccomini, Nicola Messina, Claudio Gennaro, Fabrizio Falchi, "Combining EfficientNet and Vision Transformers for Video Deepfake Detection," arXiv preprint arXiv:2107.02612, Jul. 2021. Accessed on: Jun. 27, 2025. \[Online]. Available: https://arxiv.org/abs/2107.02612

5. Yuezun Li, Xin Yang, Pu Sun, Honggang Qi, Siwei Lyu, "Celeb-DF: A Large-scale Challenging Dataset for DeepFake Forensics," arXiv preprint arXiv:1909.12962, Sep. 2019. Accessed on: Jun. 27, 2025. \[Online]. Available: https://arxiv.org/abs/1909.12962

6. Tal Reiss, Bar Cavia, Yedid Hoshen, "Detecting Deepfakes Without Seeing Any," arXiv preprint arXiv:2311.01458, Nov. 2023. Accessed on: Jun. 27, 2025. \[Online]. Available: https://doi.org/10.48550/arXiv.2311.01458

7. Felix Juefei-Xu, Run Wang, Yihao Huang, Qing Guo, Lei Ma, Yang Liu, "Countering Malicious DeepFakes: Survey, Battleground, and Horizon," arXiv preprint arXiv:2103.00218, Mar. 2021. Accessed on: Jun. 27, 2025. \[Online]. Available: https://arxiv.org/abs/2103.00218

8. Javier Hernandez-Ortega, Ruben Tolosana, Julian Fierrez, Aythami Morales, "DeepFakesON-Phys: DeepFakes Detection Based on Heart Rate Estimation," arXiv preprint, arXiv:2006.07500. Accessed on: Jun. 27, 2025. [Online]. Available: https://arxiv.org/abs/2006.07500

9. Shahroz Tariq, Sangyup Lee, "A Convolutional LSTM Based Residual Network for Deepfake Video Detection," arXiv preprint, arXiv:2009.07480. Accessed on: Jun. 27, 2025. [Online]. Available: https://arxiv.org/abs/2009.07480

10. Darius Afchar, Vincent Nozick, Junichi Yamagishi, Isao Echizen, "MesoNet: A Compact Facial Video Forgery Detection Network," arXiv preprint, arXiv:1809.00888. Accessed on: Jun. 27, 2025. [Online]. Available: https://arxiv.org/abs/1809.00888

11. Nicolo Bonettini, Edoardo Daniele Cannas, Sara Mandelli, Luca Bondi, Paolo Bestagini, Stefano Tubaro, "Video Face Manipulation Detection Through Ensemble of CNNs," arXiv preprint, arXiv:2004.07676. Accessed on: Jun. 27, 2025. [Online]. Available: https://arxiv.org/abs/2004.07676

12. Zhi Wang, Yiwen Guo, Wangmeng Zuo, "Deepfake Forensics via an Adversarial Game," arXiv preprint, arXiv:2103.13567. Accessed on: Jun. 27, 2025. [Online]. Available: https://arxiv.org/abs/2103.13567

13. Jiameng Pu, Neal Mangaokar, Lauren Kelly, Parantapa Bhattacharya, Kavya Sundaram, Mobin Javed, Bolun Wang, Bimal Viswanath, "Deepfake Videos in the Wild: Analysis and Detection," arXiv preprint, arXiv:2103.04263. Accessed on: Jun. 27, 2025. [Online]. Available: https://arxiv.org/abs/2103.04263

14. Ruben Tolosana, Ruben Vera-Rodriguez, Julian Fierrez, Aythami Morales, Javier Ortega-Garcia, "DeepFakes and Beyond: A Survey of Face Manipulation and Fake Detection," arXiv preprint, arXiv:2001.00179. Accessed on: Jun. 27, 2025. [Online]. Available: https://arxiv.org/abs/2001.00179

15. Hong-Shuo Chen, Mozhdeh Rouhsedaghat, Hamza Ghani, Shuowen Hu, Suya You, C.-C. Jay Kuo, "DefakeHop: A Light-Weight High-Performance Deepfake Detector," arXiv preprint, arXiv:2103.06929. Accessed on: Jun. 27, 2025. [Online]. A

Marine Debris Detection and Classification using Deep Learning Techniques: A Comparative Study

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ABSTRACT

Marine debris poses a significant threat to aquatic ecosystems, impacting marine life and contributing to environmental degradation. This paper provides a comprehensive review of deep learning techniques for detecting and classifying marine debris, focusing on models such as YOLO, Faster R-CNN, and SSD. Unlike previous studies, this work emphasizes practical implementation challenges, including dataset standardization, environmental complexities, and real-world applicability. The findings highlight the need for robust models and standardized datasets to enhance the effectiveness of AI-driven monitoring systems. Additionally, recommendations for improving model performance in diverse marine environments are provided, offering valuable insights for future research.

KEYWORDS *: Marine debris detection, Waste classification, Machine learning, CNNs, Deep learning, AI, Aquatic environment.*

INTRODUCTION

The increasing accumulation of marine debris, particularly plastic waste, has become a critical environmental issue, threatening biodiversity and disrupting aquatic ecosystems. The ocean can provide the lifeblood of the world and many species survive because of it. The ocean controls the climate and it also regulates carbon in the atmosphere. However, excessive pollution of the ocean has caused the ocean's ability to maintain these things to be damaged, because the majority of this trash is plastic. This is becoming increasingly severe, thus each year, up to 2.41 million tons of garbage enters the ocean (Sinthia, 2023).

This is very bad, so we need to solve this. A new computer tool can help, and it is called "deep learning", which works very well to find trash in the sea, therefore it helps in many kinds of water (Shivaanivarsha et al., 2024; Khriss et al., 2024). We can use it with cameras in the sky, or undersea drones, or autonomous boats, so that we can see all the trash in the sea. We do not need to watch by hand, because we have models that can find trash, and they can find it on the water, or on the shore, or under the water (Srilatha et al., 2023). They use a tool called CNN, which allows them to learn from other tools, but it is difficult to detect trash in dynamic oceans (Vijayanti et al., 2023).

We also have SSD, which helps detect trash that floats, or trash that is submerged (Vedant Kumar et al., 2023), and this paper reviews all these tools, thus it demonstrates how they can be used by the whole world.

Recent advancements in deep learning have shown promise in addressing this challenge by enabling automated detection and classification of marine debris. However, the effectiveness of these models is often hindered by factors such as variations in water quality, lack of standardized datasets, and environmental complexities. This paper aims to provide a review on the comparative analysis of state-of-the-art deep learning models, including YOLO, Faster R-CNN, and SSD, to evaluate their performance in detecting marine debris under diverse conditions.

LITERATURE ANALYSIS

To do this, we reviewed relevant previous studies and focused on those that reported unambiguous results on detecting marine litter by AI models and those whose

experimental methodologies were sufficiently specified to allow replication, and such studies provided useful details on the research environment, data, detection methodology, and model performance results.

Ali and Zhang (2024) provides a detailed overview of the YOLO object detection framework, its applications, and performance, demonstrating its suitability for real-time marine litter detection, and thus, it highlights the potential of the YOLO framework for various applications. Đuraš et al. (2024) describes the creation of a dataset for underwater marine debris detection and segmentation in shallow waters, which can be used to train and evaluate AI models for marine litter detection, because this dataset provides a valuable resource for researchers and developers. Shivaanivarsha et al. (2024) discussed WAVECLEAN, which is a tracking and navigating system for an autonomous ship, and it provides real-time floating debris collection, so this demonstrates the implementation of AI on marine litter collection. Khriss et al. (2024) applied deep learning to detect plastic debris underwater, and they investigated the visual characteristics of submerged plastics, therefore, this research demonstrates the application of AI on underwater litter monitoring.

Walia and PL (2023) conducted a survey of recent deep learning techniques for underwater trash detection, and they also discussed the potential applications of these techniques in autonomous robotic systems, thus, providing a comprehensive overview of the current state of underwater trash detection. Sinthia (2023) proposed a deep learning model for real-time underwater debris detection, and this paper demonstrates the application of artificial intelligence for detecting marine litter in real-time, because it highlights the potential of AI for real-time monitoring. Vijayanti et al. (2023) conducted a comparative analysis of deep learning models for garbage detection in water bodies, and they found that transfer learning with pre-trained deep learning models (such as ResNet50 and VGG19) performed the best, so this study provides valuable insights into the performance of different deep learning models. Winans et al. (2023) applied deep learning models to detect stranded marine debris at the shoreline, and their study is based on remote sensing imagery, therefore, the work provided a new insight into the potential application of AI for large-area monitoring of marine litter. Kumar et al. (2023) applied the SSD object detection model to detect marine litter, and they demonstrated that the lightweight model can be used to detect marine litter, because it is efficient and effective.

Srilatha et al. (2023) used the Faster R-CNN model for solid waste detection and recognition, and the authors concluded that Faster R-CNN is a promising method for marine litter detection, thus, it highlights the potential of the Faster R-CNN model for various applications. Abdu and Mohd Noor (2022) presented a survey on solid waste detection and classification using deep learning techniques, and the authors reviewed the latest techniques used for solid waste detection and classification, and they discussed the future trends, so this survey provides a comprehensive overview of the current state of solid waste detection and classification. Córdova et al. (2022) compared deep learning models for detecting litter, and the authors compared the performance of different deep learning models for litter detection, and they concluded that certain models are more effective than others, therefore, this study provides valuable insights into the performance of different deep learning models. Aleem et al. (2022) performed marine debris target classification using deep learning networks, and it was proven to be efficient to differentiate various kinds of marine litter, because it highlights the potential of deep learning networks for marine debris target classification.

REVIEW METHODOLOGY

The methodology for this comparative analysis draws on multiple datasets, including TrashCan, DeepTrash, TACO, PlatOPol, and FLS. Research articles were selected using specific filters related to Satellite Imagery. The study centers on evaluating Deep Learning models such as YOLO, Faster R-CNN, and SSD.

Deep Learning Model Selection

YOLO

YOLO, YOLOv3, YOLOv5, YOLOv6, YOLOv8, Tiny YOLO, YOLOv5-Ghost, and YOLOv4-Ghost are excellent for real-time object detection, and they perform detection with a single pass through the network, and are thus extremely fast. YOLO divides the image into a grid, and each grid cell predicts boxes and class scores, because this allows YOLO to be extremely fast with very good accuracy and efficiency.

Faster R-CNN

Faster R-CNN employs a two-stage detection pipeline and it generates region proposals to identify potential object locations. Then, it refines and classifies these proposals in the second stage (Srilatha et al., 2023), because it is accurate and reliable, but its two-stage pipeline makes it slower than other models. Faster R-CNN employs a ResNet backbone for feature extraction, thus this leads to a much better detection (Aleem et al., 2022).

SSD (Single-Shot detector)

The advanced architecture of SSD offers accurate detection results along with fast processing due to its unique structural design. SSD performs object detection efficiently by embedding the detection process within a single deep neural network, similar to the operational style of YOLO.

Model Training

The deep learning models in the study were trained on high-performance GPUs using popular deep learning frameworks like TensorFlow and PyTorch, and transfer learning was a critical technique in marine litter detection because of the challenge of acquiring large labelled datasets (Khriss et al., 2024). Transfer learning's greatest advantage is reducing the risk of overfitting, which is common with limited data, so training procedures involve custom loss functions, such as classification loss and bounding box regression loss to fine-tune the models, therefore, for YOLO and Faster R-CNN, these procedures are crucial.

Model Performance

YOLO

YOLOv6 is a nice algorithm and it was evaluated on the "SeaClear Marine Debris Dataset". It performed well in real-time object detection and it also consumed very less memory. Thanks to the data augmentation, smaller model size and efficient detection methodology (Đuraš et al., 2024), YOLOv6 is a nice algorithm, therefore it was evaluated on the "SeaClear Marine Debris Dataset" and performed well because it consumed very less memory.

Table 1 Stratified split baseline results - YOLOv6 S (Đuraš et al., 2024)

Model	Fusion Enhancement	mAP (%)	mAR (%)
YOLOv6 S	Not Applied	68.3	75.0
YOLOv6 S	Applied	68.9	75.4

Customized dataset was created and data was collected from multiple sources, such as Trash ICRA-19, TrashCAN 1.0, TrashNet, Google, Extended TACO, Drinking Waste, and Classify-waste. The dataset consisted of 10,000 images because the size of the image was 416 x 416 pixels. Images were divided into 3 categories, thus they were Underwater Trash, Rover, and Marine Life. The model was trained on the dataset, therefore it detected garbage. It detected garbage and it drew rectangles around the garbage. Its confidence was >=0.5 (Walia & PL, 2023) because YOLOv8-nano performed excellently. YOLOv8-nano performed excellently, so it was capable of detecting epipelagic garbage in real-time. It had high confidence scores, thus you can see the confidence scores in Table 2 (Walia & PL, 2023).

Table 2: Performance comparison for the various architectures- YOLO (Walia & PL, 2023)

Network	mAP	Precision	Recall	Box-Loss	Cls-Loss	Obj-Loss	Epoch
YOLOv8n	0.96	0.94	0.92	0.022	0.0005	0.011	170
YOLOv7	0.96	0.96	0.93	0.019	0.0005	0.008	120
YOLOv6s	0.90	0.94	0.92	0.080	0.0700	0.450	110
YOLOv5s	0.96	0.95	0.93	0.020	0.0000	0.000	180

YOLOv5 and YOLOv8 were evaluated on COCO dataset, and these models are not suitable for running on low-power computers such as Raspberry Pi 4 (8 GB RAM) for video streaming as they only achieve 4-5 fps (Shivaanivarsha et al., 2024). The results are presented in Table 3, therefore, they can be used for further analysis.

Table 3 Model Comparison of YOLOv5 and YOLOv8 (Shivaanivarsha et al., 2024)

Model	Training Accuracy (%)	Frame Rate (FPS)	Real-world Confidence Rate (%)
YOLOv5	87	4 to 5	79–87 avg
YOLOv8	90	4 to 5	80–90 avg

YOLOv8 and YOLOv9 were implemented on the "TrashCAN" dataset. Table 4 displays the results (Khriss et al., 2024).

Table 4: Accuracy Evaluation of the YOLO model using TrashCAN dataset (Khriss et al., 2024)

Model	Precision (%)	Recall (%)	mAP 0.5 (%)	mAP 0.95 (%)
YOLOv8	77.15	81.90	85.28	71.90
YOLOv9	77.76	82.14	85.33	72.48

The Forward-Looking Sonar Marine Debris Dataset (FLS) was chosen to classify and categorize types of garbage, and it consists of 1,868 images. The image resolution is 512x384 pixels, so it provides a clear view of the objects. Trash-ICRA19 was used to detect objects, therefore it has a large dataset. There are 7,668 images and 6,706 annotations, thus making it a comprehensive collection. It classifies garbage into three categories: plastic pollution, man-made objects, and nature/biology (Sinthia, 2023), because this categorization is essential for effective waste management.

Table 6 Performance Measures of Underwater Object Detection (Sinthia, 2023)

Models	AP (%)	Precision (%)	Sensitivity (%)	F1 (%)
YOLOv8	92.2	81.4	82.0	81.66
YOLOv5-ghost	84.4	80.0	68.0	73.52
YOLOv4-ghost	76.8	74.0	59.0	65.68
YOLOX-Tiny	71.3	71.5	76.7	73.80

Table 6 presents the performance metrics of different object detection models used for underwater object identification. YOLOv8 outperforms the others in underwater detection, making it the ideal choice for precise tasks. However, YOLOX-Tiny is also a viable option due to its efficiency in resource-limited environments (Sinthia, 2023).

Litter detection performance of YOLO models on the PlastOPol dataset is presented in Table 7 (Córdova et al., 2022).

Table 7: Litter Detection results on PlastOPol using YOLO models (Córdova et al., 2022)

Methods	AP50	AP@	AR@	F1@
YOLO-v5s	79.9	62.4	76.9	68.9
YOLO-v5x	84.9	71.1	82.1	76.2

Using the "TACO" dataset, the YOLO model yields the results given in Table 3.3.1.8 (Córdova et al., 2022).

Table 8 Litter Detection results on TACO using YOLO models (Córdova et al., 2022)

Methods	AP50	AP@	AR@	F1@
YOLO-v5s	54.7	38.8	58.1	46.5
YOLO-v5x	63.3	48.4	66.4	56.0

Faster RCNN

The first results for marine debris detection were obtained on the 'SeaClear Marine Debris Dataset' with Faster RCNN , and Faster RCNN is a two-step approach. It requires high computational resources in order to achieve good performance (Đuraš et al., 2024), therefore it needs to be optimized for practical applications.

Table 9. Stratified split baseline results - Faster RCNN R50 + FPN (Đuraš et al., 2024)

Model	Fusion Enhancement	mAP (%)	mAR (%)
Faster RCNN R50 + FPN	Not Applied	61.7	68.1
Faster RCNN R50 + FPN	Applied	59.0	63.6

Using the same custom dataset that was considered for Table 2 the following results were observed for Faster RCNN. These results are displayed in Table 10.

Table 10 Performance comparison for the various architectures-Faster RCNN (Walia & PL, 2023)

Network	mAP	Precision	Recall	Box-Loss	Cls-Loss	Obj-Loss	Ep-och
Faster R-CNN	0.81	0.88	0.85	0.08	0.03	0.02	100

Faster RCNN was implemented on the "TrashCAN" dataset, the results of which are displayed in Table 11 (Khriss et al., 2024).

Table 11: Accuracy Evaluation of the Faster RCNN model using TrashCAN dataset (Khriss et al., 2024)

Model	Precision (%)	Recall (%)	mAP 0.5 (%)	mAP 0.95 (%)
Faster RCNN	85.9	84.52	88.88	69.00

Using the "Deep Trash" dataset, the Faster RCNN model yields the results given in Table 12 (Khriss et al., 2024).

Table 12: Accuracy Evaluation of the Faster RCNN model using Deep Trash dataset (Khriss et al., 2024)

Model	Precision (%)	Recall (%)	mAP 0.5 (%)	mAP 0.95 (%)
Faster RCNN	75.85	79.77	84.23	69.00

Litter detection performance of Faster RCNN models on the PlastOPol dataset is presented in Table 13 (Córdova et al., 2022).

Table 13 Litter Detection results on PlastOPol using Faster RCNN model(Córdova et al., 2022)

Methods	AP50	AP@	AR@	F1@
Faster R-CNN	75.3	49.6	57.0	53.0

Using the "TACO" dataset, the Faster RCNN model yields the results given in Table 14 (Córdova et al., 2022).

Table 14 Litter Detection results on TACO using Faster RCNN models (Córdova et al., 2022)

Methods	AP50	AP@	AR@	F1@
Faster R-CNN	51.1	28.1	36.9	31.9

SSD

SSD was implemented on the "TrashCAN" dataset, the results of which are displayed in Table 15 (Khriss et al., 2024).

Table 15 Accuracy Evaluation of the SSD model using TrashCAN dataset (Khriss et al., 2024)

Model	Precision (%)	Recall (%)	mAP 0.5 (%)	mAP 0.95 (%)
SSD	86.55	84.00	87.37	68.40

SSD was implemented on the "Deep Trash" dataset, the results of which are displayed in Table 16 (Khriss et al., 2024).

Table 16 Accuracy Evaluation of the SSD model using Deep Trash dataset (Khriss et al., 2024)

Model	Precision (%)	Recall (%)	mAP 0.5 (%)	mAP 0.95 (%)
SSD	74.59	79.28	84.44	68.57

The SSD algorithm was implemented in Python to create a monitoring system, developed within Visual Studio version 20 (Vedant Kumar et al., 2023). Table 17 demonstrates that the SSD model performs effectively for real-time object detection. However, its performance may fluctuate when applied under unstable underwater conditions.

Table 17 SSD's effectiveness in high-confidence object detection (Vedant Kumar et al., 2023)

Objects Detected	Confidence (%)
Monitor Screen	99.92
Chair	97.85
Monitor (again)	79.03
Person (1)	99.91
Person (2)	98.02
Overall Accuracy	99.00

Model Comparison

The baseline evaluation was performed on the "SeaClear Marine Debris Dataset" and the dataset was split between 80% for training and 20% for testing. Table 1 shows that YOLO had the best performance among the models, because YOLOv6 S was 7% ahead of Faster R-CNN (Table 9, Đuraš et al., 2024). The selected models had good F1 and high mean average precision at different speeds (Table 2, Table 9), thus the results from the trade-off analysis are more realistic to evaluate underwater performance. The localization performance can be better evaluated, therefore the F1 scores of these models were much better than other algorithms (Walia & PL, 2023). YOLOv9 was the most effective object detection model applied to the "TrashCAN" and "Deep Trash" datasets in Tables {4, 5, 11, 12, 15, 16}, and it was better than YOLOv8, Faster R-CNN, and SSD (Khriss et al., 2024).

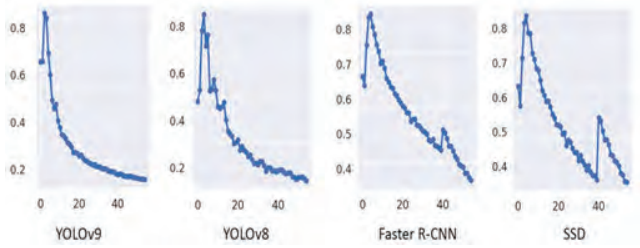

Fig 1. Training Stability of YOLOv9, YOLOv8

The evaluation metrics are shown in Fig. 3.4.1, and YOLOv9 achieves the best performance, using Programmable Gradient Information (PGI) and Generalized Efficient Layer Aggregation Network (GELAN). It is fast and accurate with a smooth loss function curve, thus it outperforms other models. YOLOv8 is also good, but it has convergence issues, because it struggles with certain types of data. Faster R-CNN uses a Region Proposal Network (RPN) for object detection, but it also has convergence issues, therefore it is not the best choice. SSD has the worst performance, with an unstable loss curve and poor adaptability, so it is not suitable for this task.

It is poor for marine object detection (Khriss et al., 2024), and this is evident from the results. Tables 3.3.1.7 and 3.3.2.5 demonstrate YOLOv5x best on the PlastOPol dataset, because it has a high accuracy rate. YOLO-based models perform well on underwater litter detection, thus they are a good choice for this application. Tables 3.3.1.8 and 3.3.2.6 demonstrate YOLOv5x best on the TACO dataset, and this is due to its robust features. YOLOv5x performs well on real-world waste detection (Córdova et al., 2022), therefore it has the potential for practical applications

DISCUSSION

There is insufficient homogenous data and this resulted in difficulties in applying models across multiple sites. Using small, custom data sets leads to poor generalisation across other locations, because (Đuraš et al., 2024) datasets are often labelled differently. This makes it difficult to compare work from different regions, thus (Vijayanti et al., 2023) most data are collected from coastal or relatively shallow waters, and there are few data from the deep sea or offshore, therefore (Winans et al., 2023) greater volume of homogenous data could be freely available to all users.

Various factors present in the water affect the performance of models in different ways, so this limits the generalizability of models in various environments. Factors such as water turbidity, exposure, and occlusion have been shown to cause decrease in model performance, because (Srilatha et al., 2023) YOLO has been demonstrated to have high inference speed, but poor detection accuracy on small objects, and (Khriss et al., 2024) Faster R-CNN has been proven to have extremely high detection accuracy, but low inference speed, thus (Vijayanti et al., 2023) SSD has been shown to have high inference speed and high detection accuracy, but poor detection of small or occluded objects, therefore (Vedant Kumar et al., 2023) to improve generalizability of models, models that employ an ensemble of other models and transfer learning schemes, are able to improve generalizability across different environments. For autonomous detection of marine debris, inference speed is critical, but the use of high resolution data and model training increases inference time, so (Shivaanivarsha et al., 2024) models must be designed to balance these competing demands.

Models such as You Only Look Once (YOLO) and Single Shot Detector (SSD) are fast but do not detect objects as well, because (Vedant Kumar et al., 2023) deploying models on small computers located near the edge, where data is generated, is challenging, and this implies that models must be designed to be more efficient and consume less energy, thus models must balance inference speed and detection accuracy, and therefore model design is critical for successful deployment.

CHALLENGES IN MARINE DEBRIS DETECTION USING DEEP LEARNING

Deep learning does not perform well in marine environments and underwater visibility is low. It is dark and it is murky, because debris is difficult to see. Visibility is difficult due to light and dirt, thus it is difficult to generalize from one body of water to another. Models trained on clear ocean water do not perform well in dirty lakes or rivers, therefore image enhancement and data augmentation are two approaches to address this issue.

Merging visible and infrared images is a possible solution, so such solutions may help, but they are not always effective. Even enhanced images may not

perform well in unseen environments, because a major issue is the lack of large and high-quality labeled datasets. There are several labeled datasets such as TrashCAN and MARIDA, but they do not cover all underwater environments, thus the model learned too much from these datasets. The models perform well during training, but perform poorly in unseen environments, because they are not able to generalize well.

There is a need for more types of litter, waterways and locations to be added to these datasets, therefore this need must be addressed in order to improve the performance of deep learning models in marine environments

CONCLUSION

This research serves as a comprehensive comparative review of various deep learning techniques for detecting and classifying marine debris. The findings indicate that while YOLO-based models excel in terms of efficiency, two-stage detectors like Faster R-CNN offer better productivity but lack real-time application suitability due to their inefficiency.

Despite these advancements in deep learning models, the study emphasizes the need for larger and more varied datasets, as well as improved methods to address domain shifts caused by environmental factors such as water clarity and lighting changes. Ultimately, deep learning techniques provide a powerful solution for marine debris monitoring, and their ability to operate in real-time makes them scalable, offering significant potential to support global efforts to protect the world's oceans.

REFERENCES

1. Đuraš A, Wolf BJ, Ilioudi A, Palunko I, De Schutter B (2024) A dataset for detection and segmentation of underwater marine debris in shallow waters. Sci Data 11:921. https://doi.org/10.1038/s41597-024-03759-2
2. Walia JS, PL K (2023) Deep learning innovations for underwater waste detection: an in-depth analysis. In: Towards autonomous robotic systems. Springer Nature, pp 292–303. https://doi.org/10.1007978-3-031-43360-3_24
3. Shivaanivarsha N, Vijayendiran AG, Prasath MA (2024) WAVECLEAN – an innovation in autonomous vessel driving using object tracking and collection of floating debris. 2024 International Conference on Communication, Computing, and Internet of Things (IC3IoT), pp 1–6. https://doi.org/10.1109/IC3IoT60841.2024.10550352
4. Khriss A, Elmiad AK, Badaoui M, Barkaoui AE, Zarhloule Y (2024) Exploring deep learning for underwater plastic debris detection and monitoring. J Ecol Eng 25:58–69
5. Sinthia AK (2023) A deep learning application for real-time debris detection: underwater environment. 2023 International Conference on Computer and Information Technology (ICCIT). https://doi.org/10.1109/ICCIT2023.00055
6. Vijayanti V, et al. (2023) Analysis of deep learning-based garbage detection in water bodies. 2023 5th International Conference on Inventive Research in Computing Applications (ICIRCA). https://doi.org/10.1109/ICIRCA2023.00055
7. Winans WR, Chen Q, Qiang Y, Franklin EC (2023) Large-area automatic detection of shoreline stranded marine debris using deep learning. Int J Appl Earth Obs Geoinf 124:103515. https://doi.org/10.1016/j.jag.2023.103515
8. Srilatha J, Subashini TS, Vaidehi K (2023) Solid waste detection and recognition using Faster RCNN. Indian J Sci Technol 16:3778–3785. https://doi.org/10.17485/IJST/v16i42.2005
9. Abdu H, Mohd Noor MH (2022) A survey on waste detection and classification using deep learning. IEEE Access 10:128151–128163. https://doi.org/10.1109/ACCESS.2022.3226682
10. Córdova M, Pinto A, Hellevik CC, Alaliyat SA-A, Hameed IA, Pedrini H, Torres RdS (2022) Litter detection with deep learning: a comparative study. Sensors 22:548. https://doi.org/10.3390/s22020548
11. Aleem A, Tehsin S, Kausar S, Jameel A (2022) Target classification of marine debris using deep learning. Intell Autom Soft Comput 32:73–85
12. Ali ML, Zhang Z (2024) The YOLO Framework: A Comprehensive Review of Evolution, Applications, and Benchmarks in Object Detection. Computers, 13(12), 336.
13. V. Kumar, V. Goel, A. Amoriya and A. Kumar, "Object Detection Using SSD," 2023 5th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), Greater Noida, India, 2023, pp. 743-748, doi: 10.1109/ICAC3N60023.2023.10541704.

Meta-Learning using ProtoNet and ProtoMAML Algorithm

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ABSTRACT

Well, The aim is to explore and compare significant algorithms designed for few-shot image classification tasks within the meta-learning framework: Prototypical Networks (ProtoNet), Model-Agnostic Meta-Learning (MAML). These algorithms address the challenge of few-shot classification, which is increasingly crucial in various image recognition applications. In fields such as healthcare, where models may need to recognize rare conditions, or per-sonal digital assistants that continuously encounter new data, the ability of a model to per-form accurately with minimal examples is critical. Few-shot learning thus bridges a crucial gap by enabling models to operate effectively where labeled data is sparse, without requiring extensive retraining. The aim of this review is to examine and compare two significant meta-learning algorithms—Prototypical Networks (ProtoNet) and Model-Agnostic Meta-Learning (MAML), with a particular focus on the ProtoMAML hybrid. These approaches address the increasingly important problem of few-shot image classification, where models must perform well with minimal training data. Few-shot learning is highly relevant in domains such as healthcare, where the recognition of rare diseases requires efficient learning from limited examples. This paper outlines the theoretical foundations of ProtoNet and ProtoMAML, surveys existing literature, evaluates their strengths and weaknesses, and discusses potential future directions.

***KEYWORDS** : Meta-learning, Machine learning, Text analysis, Few-shot learning, Prototypical network.*

INTRODUCTION

The intention is to discover and compare sizable algorithms designed for few-shot photograph type responsibilities in the meta-mastering framework: Proto-typical internet-works (ProtoNet), model-Agnostic Meta-gaining knowledge of (MAML). these algorithms deal with the project of few-shot type, which is in-creasingly more critical in various picture popularity packages.

In fields together with healthcare, in which fashions can also need to appre-hend rare condi-tions, or private virtual assistants that constantly come across new statistics, the potential of a version to carry out correctly with minimal ex-amples is important. Few-shot learning accordingly bridges a crucial hole by permitting fashions to operate effectively in which classified data is sparse, without requiring large retraining.

Metalearning, or ”learning how to learn” focuses on the models that may soon adapt to other tasks and training with limited information, which is like human learning ability. This tutorial will focus on 3 remarkable meta-mastering algorithms that are particularly developed for few-shot classification. Prototypical Networks (Pro-toNet), version-Agnostic Meta-getting to know (MAML), and ProtoMAML are some of the FOML works. More efficient models allow in recognising new classes based on a limited number of examples, which is useful when the education data is limited or constantly shifting the academic proposes a deep analysis of the CIFAR100 dataset, creating a support and test sets based on a specific data sampling methodology to mimic the few-shot learning scenarios during training. Pro-toNet lever-a can be a long time of prototype based type that combines characteristic representations with the help of magnificence whereas MAML aims to optimize the

fashions for high level adapt ability to new activities with inner as well as outer gradient loops. ProtoMAML applies a new approach to integrate the best aspects of ProtoNet's prototype initialization and MAML's performance and balanced model performance.

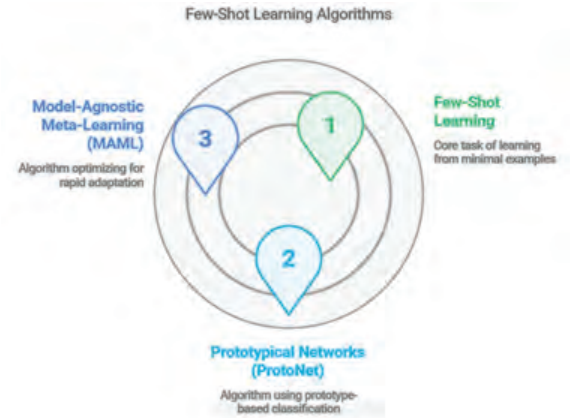

Fig. 1: Few shot Learning Algorithms

In machine learning frameworks, it is customary to have a large cohort of data for accurate generalization in a model. However, in many real-world applications, including personelized medicine, wildlife tracking, and robotic learning, getting similar extensive labeled data is not realistic. Few-shot learning tries to overcome this kind of problem by allowing models learn new concepts from a small set of labeled samples. Few-shot learning or meta-learning itself define an umbrella for learning architectures capable of learning across the distribution of tasks so that they learn quickly for unseen tasks. Learning family in this area includes but not limited to Prototypical Networks (ProtoNet) and Model-Agnostic Meta-Learning (MAML). Basically, to distinguish between different classes in ProtoNet, it uses a metric-learning approach that relies on the classification of prototypes. It is different from the above methods as it directly learns the model parameters with which new learning rates can be obtained with the help of gradients using gradient descent. ProtoMAML combines both the structural induction of ProtoNet and the optimization capability of MAML. This review paper focuses on these models from both the theoretical and empirical contexts and presents the discussion about how these models have been applied, advanced, and planned to be used version to carry out correctly with minimal ex-amples is important. Few-shot learning accordingly bridges a crucial hole by permitting fashions to operate effectively in which classified data is sparse, without requiring large retraining.

Metalearning, or "learning how to learn" focuses on the models that may soon adapt to other tasks and training with limited information, which is like human learning ability. This tutorial will focus on 3 remarkable meta-mastering algorithms that are particularly developed for few-shot classification. Prototypical Networks (ProtoNet), version-Agnostic Meta-getting to know.

RELATED WORK

Survey of Existing System

Few-shot learning allows coping with the limited training set and have thus been widely used in such scenarios. Number of examples in comparison to other traditional algorithms, for example, it is possible to easily adapt to new data without much training. This project, therefore, aims at developing a more adaptive, efficient and one that is capable of satisfying the Data Efficiency requirement but also enables expandability to domains of varying, real-life nature. Applications such as forecasting to outlier detection in the field of computer security.

Theoretical Foundations of Few-Shot Learning

The few-shot learning problems are defined as N way K shot classification task, where the purpose of the model is to classify objects into any of the N categories given only K instances of each category. Meta-learning can be of two types: meta-training, where the model learns across multiple tasks and meta-testing where the performances of multiple tasks are tested. The aim should be to design priors that can work on any task, but are fine-tuned for a specific application on hand. ProtoNet is a metric-based approach which learns the class prototypes within an embedding space. In each class \(c \), the prototype is an average of sample embeddings of the support samples of the class. Query instance is then matched to the nearest prototype based on the distance-measure which is Euclidean. This structure gives a basic but useful form of inductive bias. MAML, on the other hand, is an optimization-based method. It learns versatile approach for fast adaptation in various learning tasks which also includes time series prediction. Nichol et al. [13] further explored

first-order meta-learning algorithms like Reptile, offering computational advantages. Hospedales et al. [6] provided a comprehensive overview of the meta-learning field and its future potential in time series forecasting. Finally, Chang et al. [8] presented stock price prediction using a meta-learning algorithm with various CNN base models and a novel labeling method.

METHODOLOGY

Few-shot learning problems are usually represented as N-way K-shot learning problems in which the N class recognition has to be made with only K samples from each class. The form of meta-learning has two stages: the meta-training stage, in which the model learns across a range of tasks and the meta-testing stage where a model is assessed on tasks it has not encountered before. The desire has been to create priors that are task-neutral in nature and allow for quick and easy specializations for particular tasks. Structurally, ProtoNet is a metric-based approach that estimates class prototypes in an embedding space. In the case of each class \(c \), the prototype is defined to be the average of the embedding of all samples belonging to this class. Each query instance is assigned to the nearest prototype via the use of the distance measure known as the Euclidean distance. This brings within the present structure a clear and efficient inductive bias. MAML, on the other hand, is an optimization-based method. It identifies an initialization of the model parameters for which few updates to gradients give a good performance on the task. It is versatile in the sense that it can be used with any detectable model. The proposed method is a combination of MAML and ProtoNet that improves MAML as it initializes the last layer with the prototypes. Prototypical Networks can be performed with an embed-ding characteristic and it changes the enter pix into a characteristic space. elegance prototypes could be obtained based on the mean embed-ding of the guide samples, and new times could be classified through evaluating the distance from these prototypes. This approach is right for few-shot eventualities as it involves distance metrics as a way of handling few-shot rather than retraining with large data.

we take k examples of each class from which we derive the prototypical vectors and check the classification on all the examples.

k={2,four,eight,16,32}

model - Pretrained ProtoNet.

model data type – This is the data on which the check must be performed has to be an instance of photo Dataset.

origin - This concerns the dataset on basis of which the check must be performed. has to be an instance of photo.

data_feats -It contains the encoded features of all the images in the dataset. If None, they will be newly estimated and back. for later utilization.

k_shot - number of examples per elegance in the help set.

The curve also show s an exponential damped curve, which means that while including 2 extra examples to k=2 has a much better effect compared with when you include 2 more samples if you already have k=16; we can say that ProtoNet performs reasonably well in terms of learning new classes.

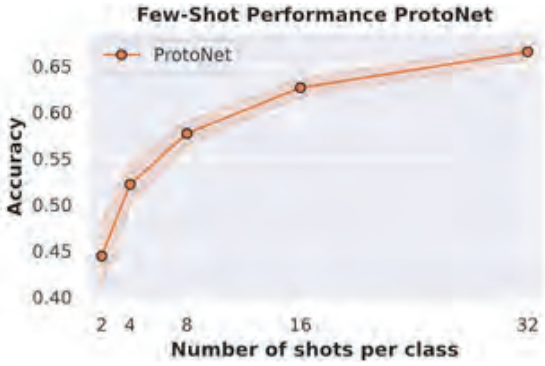

Fig. 2: Few-shot performance

The second kind of meta-mastering rules that we can consider is MAML, which stands for model-Agnostic Meta-getting to know. MAML is an optimization-based totally meta-accomplishment approach, due to this fact, it is used in an effort to change prevalent optimization manner to three-shot positioning. MAML is conceptually extremely straightforward: when training our model, we provide an answer, a help, and a query for t steps of training, and we then calculate the gradients of the question loss with respect to the parameters of the original model. For the identical version, we do it for some unique aid-question sets

and accumulate the gradients. This results in achieving a version which provides an amazing initialization of being quickly adapted to the training tasks.

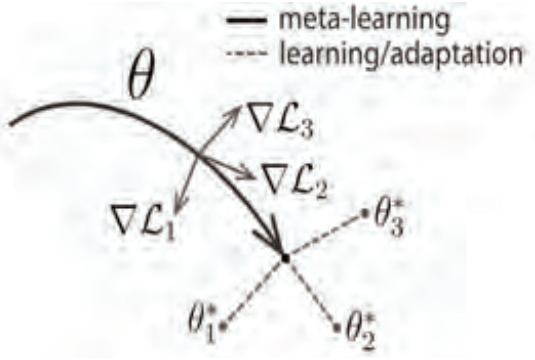

Fig. 3: Proto Model-Agnostic Meta-Learning

COMPARATIVE ANALYSIS

It performs well in cases where classes are compact and well-separated such as in the Omniglot dataset. It is fast in training and needs a small amount of computing power to implement. That is why in more complex fields like miniImageNet, intra-class variance can make a prototype less accurate. The use of MAML results in better adaptation, but at the same time it is computationally expensive compared to vanilla GDL. In this regard, ProtoMAML tries to fill these gaps. It utilizes the initialization heuristics of ProtoNet while maintaining the adaptation of MAML. Numerous works have drawn on results indicate that ProtoMAML achieves better results than both baselines, particularly in tasks that involve two or more domains or in real-world cases.

ProtoNets (Prototypical Networks)

Classifier Adaptation: ProtoNets build PSLs from scratch during the execution of the current task and based on the data that the task generates. They are obtained with respect to other tasks.

Embedding Space: At the core of the ProtoNets is the embedding function that maps any input in the support set to a feature vector.

Prototype Calculation: They compute prototypes (center of mass) for each of the classes present in the support set.

Distance-Based Classification: This is how they categorize query instances through identifying the one closest to the prototype in the embedding space.

MAML (Model-Agnostic Meta-Learning):

Initialization: MAML learns a model initialization that can be applied whenever the agent encounters new tasks.

Fast Adaptation: MAML adjusts the initialized model by performing a couple of steps of gradient descent on the support set of the new task.

Shared Weights: Specifically, MAML adapts the weights mainly from one task to another by a small amount.

Gradient-Based Approach: Weights of the model are adjusted by gradients that lead MAML to find a solution for that specific task.

APPLICATIONS AND CHALLENGES

Few-shot learning is especially applicable to healthcare (e.g., identifying new diseases), robotics (e.g., recognizing new objects), and smart personal assistants (e.g., voice recognition). Due to its excellent performance, ProtoMAML is particularly useful in such conditions, where there is a lack of data. Nevertheless, few-shot learning is still largely an open problem due to task construction, distribution shift, and representation learning. Some of the open challenges include; overfitting of the model, a problem with an imbalanced support set and the high computational costs required when using MAML.

Healthcare: In the medical field, the diagnosis power of conditions accurately especially for rare diseases, when the statistics are rather small and there are limited patients. data is available. This system's ability for a few-shot learning may empower healthcare providers to be more informed on diagnosis with very little data, thereby meaning better outcome for the patients of rare conditions and possibly less need for conducting tests in the future. for extensive, costly testing.

Finance: Predictive analytics play important role when it comes to decision making process in financial institutions and fraud detection. If there are scarce transactional information, the few-shot learning can be used in early detection of suspicious patterns. possibly mitigating fraud losses and increasing the security of

the financial systems. Moreover, when the markets are volatile, speed is most required in the adjustment of the prediction models. and such framework can offer adaptive tools to the financial analysts for making quick decisions. and accurate decisions.

Cybersecurity: As cyber-attacks are becoming more advanced, systems that can mobile offenders in real-time are also required. are necessary for securing security since they can identify the presence of new, previously unknown attacks. The few-shot learning can endow cybersecurity systems with the potential to detect novel patterns from sparse data which makes it possible to find anomalies in a timely manner which may indicate malicious activity. This flexibility allows the organizations to be able to improve their cybersecurity posture from ever-changing threats.

RESULTS AND DISCUSSION

You can observe that it is possible for Protomaml, in fact, to exceed K > 4 protonets. This is so as it is more appropriate for more samples to modify the parame-ters of the base model. Meanwhile, K = 2 protomamuru has lower perfor-mance than protonet. This is most likely connected to the fact of updating the in-ner loop of 200 where there is a danger of forming such overhang of updates.

Nevertheless, such high standard deviation of K = 2 does not allow us to come up with a statistically valid conclusion.

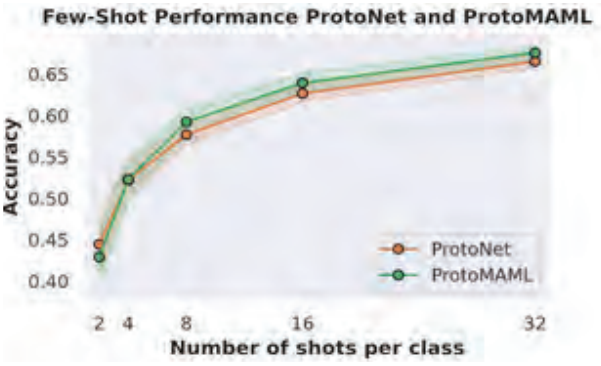

Fig. 4: Few-shot performance with ProtoNet and ProtoMAML

ProtoMAML is in par with ProtoNet for k≤4, but it is much better than ProtoNet for more than 8 shots. This is because we are able to adjust the base model which is when the data does not match the initial training data. For k=32 , ProtoMAML has 13 % better classification accuracy then Pro-toNet which begins to flatten out. From our plot below, we see the trend more clearly

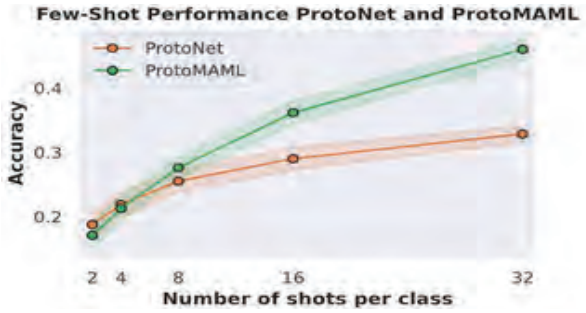

Fig. 5: Few-shot performance wrt Acurracy and number of shots per class

Taken all together, we can say that for larger shot counts, ProtoMAML beats ProtoNet slightly. However, one limitation of ProtoMAML is an increased time of training and testing. ProtoNet is simple, efficient and strong base-line for ProtoMAML and only possibly better option for cases when resources are limited.

CONCLUSION AND FUTURE WORK

Through efficient training on small size datasets, the model reaches a high accu-racy level and a generalization to unseen classes, making it adaptable. In general, the system managed to evidence the promise of meta-learning to address those challenges that are present in the real world by giving a smart, flexible solution that could even show good performance although there is a lack of data. Fulfilled the Stage-1, receiving insights into MAML, and ProtoNet algorithms. Compared MAML and Reptile with respect to LSTM, GRU, FFNN as base models.

Provided Analysis of this algorithms based on there classes. Findings provide strong ground to continue its elaboration in Stage-2. This review looked into the theoretical foundations, comparative performance, and applications of ProtoNet and ProtoMAML for few-shot learning. ProtoMAML provides a synergistic combination of the structured representation learning and adaptive fine-tuning. As time goes by, hybrid approaches that combine the strengths of metric and optimization-based learning is likely to define few-shot learning.

There are a number of ways of pushing ProtoNet and ProtoMAML forward. The combination of attention mechanisms, improving the prototype representations with contextual embeddings, and unsupervised meta-learning are promising directions. Moreover, scaling ProtoMAML to bigger architectures like transformers and evaluating its efficacy in the continual learning setup would make it more versatile. Strong evaluation over heterogeneous datasets is also essential to benchmark the progress.

REFERENCES

1. Wang, Y., & Liu, Q. (2020). Comparison of Akaike information criterion (AIC) and Bayesian information criterion (BIC) in the selection of stock- recruitment relationships. Fisheries Research, 77(2), 220-225.
2. Chakrabarti, A., & Ghosh, J. K. (2020). AIC, BIC, and recent advances in model selection. Philosophy of statistics, 583-605.
3. A.Ariyo, A. O. Adewumi, and C. K. Ayo, "Stock Price Prediction Using the ARIMA Model," 2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation, 2019, pp. 106-112, DOI: 10.1109/UKSim.2014.67.
4. Adebiyi, A. A., Adewumi, A. O., & Ayo, C. K. (2022). Comparison of ARIMA and artificial neural networks models for stock price prediction. Journal of Applied Mathematics, 2021.
5. Moosazadeh, M., Khanjani, N., Nasehi, M., & Bahrampour, A. (2021). Predicting the incidence of smear-positive tuberculosis cases in Iran using time series analysis. Iranian journal of public health, 44(11), 1526.
6. Farhath, Z. A., Arputhamary, B., & Arockiam, L. (2019). A survey on ARIMA forecasting using a time series model. Int. J. Comput. Sci. Mobile Comput, 5, 104-109.
7. Roondiwala, M., Patel, H., & Varma, S. (2019). Predicting stock prices using LSTM. International Journal of Science and Research (IJSR), 6(4), 1754-1756.
8. Brassington, G. (2023, April). Mean absolute error and root mean square error: which is the better metric for assessing model performance? In EGU General Assembly Conference Abstracts (p. 3574).
9. Ghosh, A., Bose, S., Maji, G., Debnath, N., & Sen, S. (2021, September). Stock price prediction using LSTM on Indian Share Market. In Proceedings of 32nd international conference on (Vol. 63, pp. 101-110).
10. Khairina, D. M., Daniel, Y., & Widagdo, P. P. (2021, July). Comparison of double exponential smoothing and triple exponential smoothing methods in predicting income of local water company. In Journal of Physics: Conference Series (Vol. 1943, No. 1, p. 012102). IOP Publishing.
11. Koch, G., Zemel, R., Salakhutdinov, R. (2021). Siamese Neural Networks for One-shot Image Recognition. In Proceedings of the 32nd International Conference on Machine Learning (ICML).In Advances in Neural Information Processing Systems (NeurIPS).
12. Finn, C., Abbeel, P., Levine, S. (2022). Model-Agnostic Meta-Learning for Fast
13. Chen, W. Y., Liu, Y. C., Kira, Z., Wang, Y. C. F., Huang, J. B. (2019). A Closer Look at Few-shot Classification. In International Conference on Learning Representations(ICLR).
14. Raghu, A., Raghu , M., Bengio, S., Vinyals, O. (2019). Rapid Learning or Feature Reuse? Towards Understanding the Effectiveness of MAML. In 7th International Conference on Learning Representations (ICLR).
15. Jake Snell University of Toronto ,Kevin Swersky, Twitter ,Richard S. Zemel (2022),University of Toronto, Vector Institute Prototypical Networks for Few-shot Learning.
16. Chelsea Finn, Pieter Abbeel, Sergey Levine Proceedings of the 34th International Conference on Machine Learning, PMLR 70:1126- 1135, 2020, Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks.
17. Xianyun Wen and Weibang Li, “Time series prediction based on LSTM-attention-LSTM model,” IEEE Access, pp. 1-1, 2023, doi: 10.1109/ACCESS.2023.3276628.
18. Jaehyeon Son, Soochan Lee, and Gunhee Kim, “When Meta-Learning Meets Online and Continual Learning: A Survey,” IEEE transactions on pattern analysis and machine intelligence, pp. 1-1, 2024, doi: 10.1109/TPAMI.2024.3463709.
19. Supriya Mahadevkar, Bharti Khemani, Shruti Patil, Ketan Kotecha, Deepali Vora, and Ajith Abraham, “A Review on Machine Learning Styles in Computer Vision -Techniques and Future Directions,” IEEE Access, pp. 1-1, 2022, doi:10.1109/AC-CESS.2022.3209825.

Small Models, Big Gains: Efficient Domain Specialization of Lightweight Language Models for E-commerce

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ABSTRACT

Large Language Models (LLMs) are general-purpose tools that often lack domain-specific optimization, making them less suitable for Micro, Small, and Medium Enterprises (MSMEs) in e-commerce. This study explores Small Language Models (SLMs) as efficient alternatives by fine-tuning them on the ECInstruct dataset, structured with predefined train, test, and validation splits for consistent benchmarking. Using Low-Rank Adaptation (LoRA) and QLoRA for Parameter-Efficient Fine-Tuning (PEFT), we improve model performance while minimizing resource costs. Additionally, our dataset enables Diverse and Single Instructions Testing and In Domain vs. Out of Domain Testing, ensuring robust generalization and realistic performance assessment. Results show that fine-tuned SLMs outperform larger models like GPT-4 Turbo and Gemini Pro on domain-specific benchmarks, achieving improved accuracy and relevance. These findings advocate for lightweight, specialized AI models optimized for efficiency and accessibility.

KEYWORDS *: Small language models, E-commerce, Instruction tuning, QLoRA.*

INTRODUCTION

Language models, especially large language models (LLMs), have revolutionized natural language processing (NLP) tasks across various domains. General-purpose models such as GPT-4 [1], Gemini [2], Claude [3], LLaMA 2 [4], and Mistral [5] demonstrate unprecedented capabilities in understanding and generating human language. Their impact is increasingly visible in the e-commerce sector, where specialized LLMs like EComGPT [6] and LiLiuM [7], have shown significant improvements in automation, personalization, and customer interaction, thereby enhancing business efficiency. Nonetheless, despite the efficacy of LLMs, their adoption remains limited among Micro, Small, and Medium Enterprises (MSMEs), which make up a substantial portion of the global business ecosystem—on average, 40 MSMEs per 1,000 people, with a median of 31 [8]. While MSMEs recognize the potential benefits of adopting language models—including increased efficiency, better customer service, and improved decision-making—they often face substantial barriers. These include high computational costs, data privacy concerns, and the lack of technical expertise required to train and deploy large models [9,10].

Small Language Models (SLMs) have fewer parameters than LLMs, which can range up to hundreds of billions of parameters [11]. In particular, we are exploring models in the range of 300 million to 2 billion parameters [12]. We are specifically investigating models that fall within the range of 300 million to 2 billion parameters [12]. Although these models may not match LLMs in terms of generalization, they demonstrate effectiveness when fine-tuned for specific applications [13]. SLMs drastically reduce the cost and hardware resources required to create language models capable of completing such domain-specific tasks [14,15]. Several studies have highlighted the effectiveness of SLMs in specialized domains, demonstrating that, with targeted fine-tuning, these models can rival larger models in accuracy and relevance. Nonetheless, their application in the e-commerce sector remains underexplored, especially

in scenarios tailored to the unique needs and constraints of MSMEs. This highlights a notable gap in the existing body of knowledge.

In this study, we address this gap by providing empirical evidence that SLMs can match or even surpass LLM performance across a range of e-commerce tasks with minimal fine-tuning. This makes them a viable, efficient, and secure option for MSMEs to adopt or build domain-specific language models suited to their individual needs.

The key Contribution in this research work includes Fine-tuning the pre-trained SLMs such as SmolLM2 and LLaMA 3.2 on ECInstruct dataset organized into ten distinct e-commerce tasks, which are classified into four overarching categories according to the nature of the tasks. For fine-tunning we adapted QLoRA, which is grounded in LoRA, a prominent technique for Parameter-Efficient Fine-Tuning (PEFT), significantly lowering computational expenses. We demonstrate that SLMs can achieve task metrics comparable to LLMs in the e-commerce domain, showing minimal performance trade-offs. We conduct detailed experiments and comparative analyses between selected SLMs and LLMs across various e-commerce NLP tasks. We highlight how MSMEs can leverage SLMs to build high-performing models independently, significantly reducing reliance on external cloud resources and minimizing cost and complexity.

LITERATURE ANALYSIS

Small Language Models (SLMs) are changing the AI landscape, proving that smaller can indeed be faster and smarter. SLMs are more efficient, inexpensive, and flexible compared with their larger counterparts, which usually require huge computational capabilities and face problems related to non-compliance and security. Studies like those of Sinha et al. (2024) highlight that SLMs show significant practical utility by performing within 10% of cutting-edge large models such as GPT-4o-mini, Gemini-1.5-Pro, and DeepSeek-v2 in a variety of tasks, domains, and reasoning types [13]. This makes SLMs a practical solution, particularly in resource-constrained environments due to faster inference and the ability for edge-device deployment. Chen et al. (2024) showcased the effectiveness of domain-specific SLMs by designing OnlySportsLM, a compact 196M parameter model optimized for sports-related tasks. They leveraged specialized datasets and the RWKV-v6 architecture to achieve competitive performance with remarkable efficiency. This approach enabled the model to rival or even exceed the performance of larger general-purpose models, proving that smaller, domain-focused models can deliver competitive results [16]. Pham et al. (2024) introduced SlimLM, which demonstrated the ability to efficiently perform on-device document assistance tasks, showcasing the prospects for SLMs in targeted applications. By determining trade-offs between model size, context length, and inference time, SlimLM was able to efficiently process on a Samsung Galaxy S24. This approach focuses on the aspect that SLMs can greatly reduce dependence on cloud systems, providing affordable and privacy-friendly solutions [14]. Similarly, Sharma et al. (2024) presented ChipNeMo, a model that exceeds the capabilities of larger counterparts like Claude 3 Opus and ChatGPT-4 Turbo while reducing the Total Cost of Ownership (TCO) by 90-95% [10].

Given these advantages, SLMs have the potential to revolutionize a number of sectors, especially eCommerce, where personalization and efficiency are critical. Language models are already automating the generation of product descriptions, solving cold-start problems, and boosting metrics like click-through rates and customer engagement. Herold et al. (2024) showed that in non-English activities, custom LLMs—like eBay's LiLiuM—outperforms general-purpose models by providing faster and more accurate text creation [7]. Furthermore, the integration of language models with visual models enhances tasks such as product matching, attribute extraction, and categorization, leading to improved search and recommendation systems. Y. Li et al. (2023) introduced instruction-tuned models such as EcomGPT, which were trained on specialized datasets designed specifically for eCommerce. These models surpass larger, general-purpose models like ChatGPT in classification, matching, and text creation due to improved generalization and zero-shot capabilities. In terms of average performance on unseen datasets, EcomGPT, even with the lowest number of parameters (560 million), outperforms ChatGPT, which has over 100 billion parameters [6]. Similarly, Peng Et Al. (2024) advanced the field with open-source initiatives like eCeLLM and datasets such as ECInstruct, which improved product matching, attribute extraction, and search categorization [17]. While these developments highlight the immense potential of SLMs, their real-world performance and applicability, particularly for Micro, Small, and Medium Enterprises (MSMEs) in eCommerce, remains underexplored. As compared to larger enterprises, smaller businesses often face barriers such as high costs and a lack of technical expertise. There is a pressing need for further research into how SLMs can be adapted for

these businesses, offering them affordable solutions that are easy to integrate with existing systems. By focusing on MSMEs, this study aims to show how smaller models can help businesses improve their operational efficiency and customer experiences, opening the path for affordable and accessible AI solutions.

METHODOLOGY

Dataset

ECInstruct is an instruction fine tuning dataset for E-Commerce tasks [17]. The dataset contains a total of 116,528 samples distributed to a total of 10 tasks. Each of these tasks are aimed to test the model on a specific task or area for which LLMs are commonly used for in E-Commerce. All of the 10 tasks can be classified into 4 high level categories based on its type.

User understanding

Sentiment Analysis (SA)

Analyze a user's product review to figure out the sentiment expressed about the item being reviewed.

Sequential Recommendation (SR)

Anticipating future products that a user may be interested in, based on their current interactions.

Product QA

Answerability Prediction (AP)

Determine whether a product-related question can be answered based on product reviews.

Answer Generation (AG)

Generate answers for product-related queries based on reviews as context.

Product Understanding

Attribute Value Extraction (AVE)

Determine the values for the particular target attributes based on the product names, descriptions, features, and brands.

Product Relation Prediction (PRP)

Models can generate better outcomes while performing other e-commerce tasks, such recommendations, by analyzing the relationships between products.

Product Matching (PM)

Determine the relationship between two items based on their titles.

Query Product Matching

Multiclass Product Classification (MPC)

Determine whether a product title and a query are appropriate (exact, substitute, complementary, or irrelevant).

Product Substitute Identification (PSI)

Evaluate whether a potentially relevant product can serve as an appropriate substitute for a given user query.

Query Product Ranking (QPR)

Determine the products' relevance to the user query by ranking them based on the query and a list of potentially related products.

Data splits

The entire dataset is divided in test, train and validation sets for each task individually. Additionally, features of the dataset are mentioned as follows.

Diverse and Single Instructions

For each task, six different types of instruction prompt, covering different language styles are present for better generalizability and understanding of tasks. Each task contains six diverse instruction prompts, where one of these is kept only for testing, thus this prompt is not seen while training.

In Domain and Out of Domain samples

The In Domain test set contains product and categories that were present during training. The Out of Domain test dataset contains a product category completely unseen by the model allowing to test for the generalizability of the model.

Model

This study employs several Small Language Models (SLMs) including SmolLM (v1 and v2) 1.7B and 360M variants, and Llama 3.2 1B [11,18–23]. These models are chosen for their performance and efficiency showcased on several benchmarks. These models, being lightweight, are suitable for local hardware and edge devices, balancing cost-effective inference with competitive language understanding. We instruction tune these pretrained SLMs on the ECInstruct dataset to create high-performing domain specific models, as shown in figure 1.

Fig. 1: Instruction tuning high level pipeline

The instruction-tuning process for small language models (SLMs) starts with a pre-trained model, such as SmolLM2 or LLaMA 3.2, which is then fine-tuned using a curated instruction dataset. The dataset provides structured inputs and expected outputs to improve the model's task-specific performance. The goal of instruction tuning is to align the model with desired behaviour using a set of prompts, making it adaptable to real-world tasks while keeping computational costs under control.

Fig 1 provides a step-by-step breakdown of the instruction-tuning process. The pipeline begins with an input command that the small language model (SLM) uses to generate an output via LLM prompting. To quantify its errors, the model compares the anticipated output to the ground truth and calculates a loss function. The loss is subsequently minimized using backpropagation, which involves modifying the model's parameters to improve accuracy and alignment with the instruction dataset. This iterative procedure allows the model to better generalize across different instruction-based tasks.

As mentioned in the Introduction, Micro, Small, and Medium Enterprises (MSMEs) lack the budget or resources to avail training on high end GPUs. To emulate such a situation we fine tuned our pre-trained models using QLoRA based on LoRA (Low-Rank Adaptation), the most widely used PEFT (Parameter Efficient Fine Tuning) technique drastically reducing the computational requirements for training. Parameter Efficient Fine-Tuning (PEFT) techniques have emerged as a crucial strategy for adapting large language models (LLMs) to new tasks without the need for extensive computational resources. These methods focus on updating a minimal set of parameters, thereby reducing both memory and computational demands. PEFT techniques like LoRA and its variants have been instrumental in making fine-tuning more accessible and efficient [24–26]. Table 1 summarizes the total and trainable parameters of the fine-tuned models. The naming convention for these models follows the format base_model_name-EC, where base_model_name represents the underlying base model used as the foundation for fine-tuning.

Table 1: Model Parameters

Model	Total params	Trainable params
smolLM2-EC	1.7B	19M
smolLM2-EC	360M	9.4M
Llama3.2-EC	1B	13M
Llama3.2-EC	3B	26.4M

LoRA is a prominent PEFT method that approximates model changes using low-rank matrices. It freezes the original model weights and updates only the low-rank adapters, which significantly reduces the number of trainable parameters. This approach has been shown to be effective across various tasks and models, providing a balance between performance and resource efficiency [27]. However, LoRA can sometimes underperform compared to full fine-tuning, especially in complex domains, prompting the development of more advanced techniques like HydraLoRA and PiSSA [26,28]. The figure 2 shows how LoRA is used in transformer blocks. QLoRA works upon this by quantizing the pre trained model weights and adding the adaptor weights which are then updated during training [29]. This drastically reduces the memory requirements of training the model making it feasible to complete training of models within the budget and resource constraints of MSMEs. This study made use of the PEFT library's implementation of QLoRA for fine tuning. Figure 3 gives a brief overview how weight updation in an adapter takes place.

Table 2: IND evaluation

Model	AVE	PRP	PM	SA	SR	MPC	PSI	QPR	AP	AG
	F1*	Macro F1	F1	Macro F1	HR@1	Accuracy	F1	NDCG	F1	F_{BERT}
GPT-4 Turbo	0.495	0.326	0.753	0.516	0.387	0.611	0.195	**0.875**	0.649	**0.858**
Gemini Pro	0.396	0.136	0.867	0.470	0.269	0.584	0.248	0.821	0.506	0.855
Claude 2.1	0.381	0.275	0.523	0.415	0.066	0.655	0.273	0.821	0.280	0.841
Llama-2 13B-chat	0.002	0.323	0.434	0.188	0.056	0.504	0.252	0.815	0.623	0.811
Mistral-7B Instruct-v0.2	0.369	0.324	0.613	0.470	0.164	0.529	0.305	0.842	0.588	0.853
EcomGPT	0.000	0.091	0.648	0.188	0.042	0.540	0.170	0.000	0.086	0.669
SmolLM2-360M-EC	0.858	0.302	0.720	0.516	0.046	0.633	-	0.809	0.794	0.852
SmolLM2-1.7B-EC	**0.988**	0.596	**0.995**	0.604	0.481	0.666	0.373	0.869	0.860	0.837
Llama3.2-1B-EC	-	0.564	0.991	0.596	0.495	0.419	0.371	0.874	0.851	0.856
Llama3.2-3B-EC	-	**0.619**	**0.995**	**0.633**	**0.526**	**0.690**	**0.420**	**0.880**	**0.861**	**0.859**

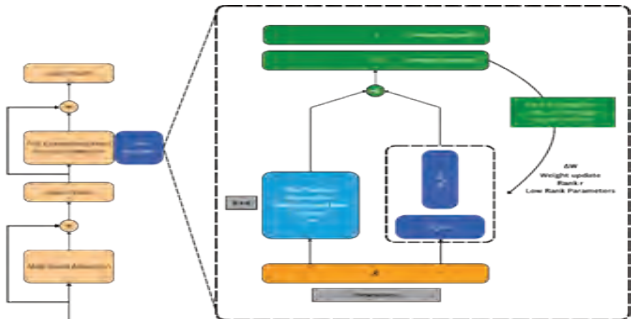

Fig. 2: Weight updation in LoRA

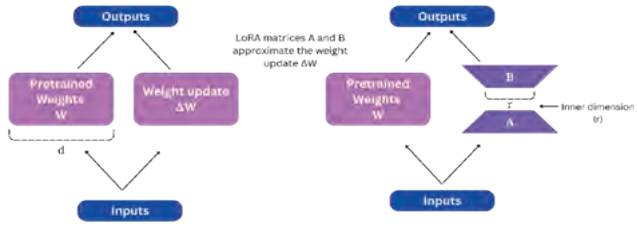

Fig. 3: Fine-tuning (left) v/s LoRA fine-tuning (right)

The left section of the figure illustrates a standard transformer block, which includes multi-head attention, layer normalization, and a feed-forward network, as well as a LoRA adaptor for efficient parameter adaptation. The right section provides a detailed view of the QLoRA fine-tuning process. The pre-trained model's weight matrix W is frozen and quantized to ensure minimal memory consumption. Instead of updating the entire weight matrix, QLoRA introduces two low-rank matrices:

$$W_A \in \mathbb{R}^{d \times r}, W_B \in \mathbb{R}^{r \times d}$$

which learn task-specific adaptations. These matrices process the input X to generate low-rank weight updates, which are then included into the model's predictions. The weight update process relies on backpropagation, adjusting the low-rank parameters ΔW based on the error between the actual output Y and predicted output Y ′:

$$\Delta W = W_A W_B$$

This technique allows for efficient fine-tuning, significantly reducing computational overhead while preserving model expressivity.

RESULTS AND DISCUSSION

Evaluation setup

General-purpose LLMs are evaluated using checkpoints given by their authors. GPT-4 Turbo [1], Gemini Pro [2], and Claude 2.1 [3] are accessed via official APIs, whereas Llama-2 13B-chat [4] and Mistral-7B Instruct-v0.2 [5] are retrieved from Hugging Face. Since in-context examples are known to improve results, the assessment uses a 1-shot setting to balance computational expense and performance. Because of their slowness and tendency to lower user interest, extensive prompt engineering and few-shot learning are considered impracticable for large-scale e-commerce applications. Also fine tuning the model for the specific tasks of the business eliminates the necessity of employing any such prompt engineering techniques.

EcomGPT is evaluated using its checkpoint, which was released by the authors [6]. Since 1-shot evaluation demonstrates better performance than 0-shot for EcomGPT, both 0-shot and 1-shot evaluations are conducted. For every assignment, the best performance from these assessments is reported. Evaluation results for both General Purpose LLMs and E-Commerce LLMs are taken as it is from the previous works of authors of ECInstruct[17].

We evaluated our models namely SmolLM2-360M-EC, SmolLM2-1.7B-EC, Llama3.2-1B-EC, and Llama3.2-7B-EC on different tasks after fine-tuning on the entire dataset for all tasks. Early results show promise as the models exhibits comparative or superior performance over much larger models than their size, in terms of parameter count and overall architecture. This comparison is with respect to other models benchmarked on the EC-Instruct dataset [17]. It encompasses several tasks aimed at improving both product and user understanding as explained in section 3.1.1. The following are preliminary results for the in-domain evaluation of some tasks from the EC-Instruct.

Table 3: Out Of Domain Evaluation

Model	AVE	PRP	SA	SR	AP	AG
	F1*	M-F1	M-F1	HR@1	F1	F_{BERT}
GPT-4 Turbo	0.397	0.392	0.510	0.198	0.680	**0.860**
Gemini Pro	0.275	0.123	0.454	0.116	0.552	0.856
Claude 2.1	0.410	0.277	0.369	0.036	0.245	0.842
Llama-2 13B-chat	0.000	0.324	0.178	0.050	0.644	0.808
Mistral-7B	0.264	0.327	0.438	0.108	0.608	0.851
Instruct-v0.2	0.264	0.327	0.438	0.108	0.608	0.851
EcomGPT	0.001	0.096	0.178	0.023	0.140	0.722
SmolLM2-360M-EC	0.659	0.200	0.503	0.044	0.832	0.856
SmolLM2-1.7B-EC	0.573	0.542	0.568	0.249	0.885	0.838
Llama3.2-1B-EC	**0.721**	0.531	0.581	0.250	**0.895**	0.856
Llama3.2-3B-EC	-	**0.550**	**0.619**	**0.265**	0.893	**0.860**

Metrics

F1* is used for Attribute Value Extraction to evaluate the balance between precision and recall, ensuring an effective

measure of the model's performance. The equations for precision*, recall*, and F1* are defined in equation below, where NV stands for Null Value, IV for Incorrect Value, CV for Correct Value, WV for Wrong Value, and NL for Null Value. Moreover, normal F1 score is used to evaluate the performance on product matching (PM), product substitute identification (PSI), and answerability prediction (AP). For sentiment analysis (SA) Macro F1 is used. Sequential recommendation (SR) is evaluated on hit rate at 1 (HR@1), which calculates whether the top-ranked product for a certain user is relevant. FBERT measures the similarity between the embeddings of the generated text and the ground-truth text.

$$\text{precision}^* = \frac{NV + CV}{NV + IV + CV + WV}$$

$$\text{recall}^* = \frac{NV + CV}{N}$$

$$F_1^* = 2 \times \frac{\text{precision}^* \times \text{recall}^*}{\text{precision}^* + \text{recall}^*}$$

$$P_t = TruePositives / (TruePositives + FalsePositives)$$

$$R_t = TruePositives / (TruePositives + FalseNegatives)$$

$$\text{Macro}-\text{F}_1 = \frac{1}{|T|} \sum_{t \in T} 2 \frac{P_t R_t}{P_t + R_t}$$

Discussions

It is evident from the results that much smaller models, with minimal fine-tuning, outperform some of the top LLMs in the current market. This indicates potential for lots of possible applications for these SLMs in various domains with modest requirements. This also aligns with a new uprising direction in LLM research, where efficiency is underscored. Using smaller language models for niche tasks can make the whole process economical along with wider ranges of devices supporting the models because of on-edge processing.

CONCLUSION

This study shows that Small Language Models (SLMs) can achieve performance comparable to general-purpose Large Language Models (LLMs) in the e-commerce domain. By fine-tuning models such as SmolLM on the EC-Instruct dataset using QLoRA, we highlight the effectiveness of parameter-efficient tuning for various e-commerce applications. Our findings demonstrate that SLMs can perform competitively in key tasks while offering a cost-effective alternative to large-scale LLMs. Evaluations on both in-domain and out-of-domain datasets further validate their adaptability and efficiency, making them a viable solution for Micro, Small, and Medium Enterprises (MSMEs). While larger models set high performance benchmarks, our study shows that well-optimized SLMs can achieve equivalent outcomes with substantially fewer resources, paving the way for future breakthroughs in specialized AI solutions for MSMEs.

REFERENCES

1. J. Achiam, S. Adler, S. Agarwal, L. Ahmad, I. Akkaya, F. L. Aleman, D. Almeida, J. Altenschmidt, S. Altman, S. Anadkat, et al., Gpt-4 technical report, arXiv preprint arXiv:2303.08774 (2023).
2. G. Team, R. Anil, S. Borgeaud, J.-B. Alayrac, J. Yu, R. Soricut, J. Schalkwyk, A. M. Dai, A. Hauth, K. Millican, et al., Gemini: a family of highly capable multimodal models, arXiv preprint arXiv:2312.11805 (2023).
3. Anthropic, Model card for claude 2, https://www-cdn.anthropic.com/bd2a28d2535bfb0494cc8e2a3bf135d2e7523226/Model-Card-Claude-2.pdf, accessed: 2025-01-07 (2023).
4. H. Touvron, L. Martin, K. Stone, P. Albert, A. Almahairi, Y. Babaei, N. Bashlykov, S. Batra, P. Bhargava, S. Bhosale, et al., Llama 2: Open foundation and fine-tuned chat models, arXiv preprint arXiv:2307.09288 (2023).
5. A. Q. Jiang, A. Sablayrolles, A. Mensch, C. Bamford, D. S. Chaplot, D. d. l. Casas, F. Bressand, G. Lengyel, G. Lample, L. Saulnier, et al., Mistral 7b, arXiv preprint arXiv:2310.06825 (2023).
6. Y. Li, S. Ma, X. Wang, S. Huang, C. Jiang, H.-T. Zheng, P. Xie, F. Huang, Y. Jiang, Ecomgpt: Instruction-tuning large language models with chain-of-task tasks for e-commerce, in: Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 38, 2024, pp. 18582–18590.
7. C. Herold, M. Kozielski, L. Ekimov, P. Petrushkov, P.-Y. Vandenbussche, S. Khadivi, Lilium: ebay's large language models for e-commerce, arXiv preprint arXiv:2406.12023 (2024).
8. K. Haider, M. Khanna, M. Kotei, K. Kushnir, S. Singh, T. Sridhar, Micro, small and medium enterprises - economic indicators (msme-ei), Tech. rep., International Finance Corporation (2019).

9. S. Gowda, Ai catalyst: Cracking the code for msme productivity (2024).

10. A. Sharma, T.-D. Ene, K. Kunal, M. Liu, Z. Hasan, H. Ren, Assessing economic viability: A comparative analysis of total cost of ownership for domain-adapted large language models versus state-of-the-art counterparts in chip design coding assistance (2024). arXiv:2404.08850. URL https://arxiv.org/abs/2404.08850

11. E. B. Loubna Ben Allal, Anton Lozhkov, The rise of small language models (slms), Hugging Face Blog (2023). URL https://huggingface.co/blog/smollm

12. S. Beatty, The phi-3: Small language models with big potential, Microsoft Source Feature (2023). URL https://news.microsoft.com/source/features/ai/the-phi-3-small-language-models-with-big-potential/

13. N. Sinha, V. Jain, A. Chadha, Are small language models ready to compete with large language models for practical applications?, arXiv preprint arXiv:2406.11402 (2024).

14. T. M. Pham, P. T. Nguyen, S. Yoon, V. D. Lai, F. Dernoncourt, T. Bui, Slimlm: An efficient small language model for on-device document assistance, arXiv preprint arXiv:2411.09944 (2024).

15. R. Yi, X. Li, W. Xie, Z. Lu, C. Wang, A. Zhou, S. Wang, X. Zhang, M. Xu, Phonelm: an efficient and capable small language model family through principled pre-training, arXiv preprint arXiv:2411.05046 (2024).

16. Z. Chen, C. Li, X. Xie, P. Dube, Onlysportslm: Optimizing sports-domain language models with sota performance under billion parameters, arXiv preprint arXiv:2409.00286 (2024).

17. L. Peng, et al., ecellm: Generalizing large language models for e-commerce from large-scale, high-quality instruction data, Paper (2024).

18. L. B. Allal, A. Lozhkov, E. Bakouch, Smollm - blazingly fast and remarkably powerful (Jul 2024). URL https://huggingface.co/blog/smollm

19. P. Clark, I. Cowhey, O. Etzioni, T. Khot, A. Sabharwal, C. Schoenick, O. Tafjord, Think you have solved question answering? try arc, the ai2 reasoning challenge, arXiv:1803.05457v1 (2018).

20. T. Mihaylov, P. Clark, T. Khot, A. Sabharwal, Can a suit of armor conduct electricity? a new dataset for open book question answering, in: EMNLP, 2018.

21. R. Zellers, A. Holtzman, Y. Bisk, A. Farhadi, Y. Choi, Hellaswag: Can a machine really finish your sentence?, in: Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, 2019.

22. A. Talmor, J. Herzig, N. Lourie, J. Berant, CommonsenseQA: A question answering challenge targeting commonsense knowledge, in: Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), Association for Computational Linguistics, Minneapolis, Minnesota, 2019, pp. 4149–4158. arXiv:1811.00937, doi:10.18653/v1/N19-1421. URL https://aclanthology.org/N19-1421

23. D. Hendrycks, C. Burns, S. Basart, A. Zou, M. Mazeika, D. Song, J. Steinhardt, Measuring massive multitask language understanding, Proceedings of the International Conference on Learning Representations (ICLR) (2021).

24. K. Cobbe, V. Kosaraju, M. Bavarian, M. Chen, H. Jun, L. Kaiser, M. Plappert, J. Tworek, J. Hilton, R. Nakano, C. Hesse, J. Schulman, Training verifiers to solve math word problems, arXiv preprint arXiv:2110.14168 (2021).

25. A. Chavan, Z. Liu, D. Gupta, E. Xing, Z. Shen, One-for-all: Generalized LoRA for parameter-efficient fine-tuning (2023). arXiv:2306.07967.

26. M. Thakkar, Q. Fournier, M. D. Riemer, P.-Y. Chen, A. Zouaq, P. Das, S. Chandar, A deep dive into the trade-offs of parameter-efficient preference alignment techniques (2024). arXiv:2406.04879.

27. S. Chen, Y. Ju, H. Dalal, Z. Zhu, A. Khisti, Robust federated finetuning of foundation models via alternating minimization of LoRA (2024). arXiv:2409.02346.

28. E. J. Hu, Y. Shen, P. Wallis, Z. Allen-Zhu, Y. Li, S. Wang, L. Wang, W. Chen, Lora: Low-rank adaptation of large language models (2021). arXiv:2106.09685. URL https://arxiv.org/abs/2106.09685

29. F. Meng, Z. Wang, M. Zhang, PiSSA: Principal singular values and singular vectors adaptation of large language models (2024). arXiv:2404.02948.

30. C. Tian, Z. Shi, Z. Guo, L. Li, C. Xu, HydraLoRA: An asymmetric LoRA architecture for efficient fine-tuning (2024). arXiv:2404.19245.

A Framework for Enhancing Model Transparency to Address Opacity and Data Bias in Complex Machine Learning Models

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ABSTRACT

As Machine Learning (ML) models are becoming more accurate and sophisticated, the opacity of these models presents a significant challenge to its users while comprehending their decision-making process, particularly in the critical domain like healthcare, finance and criminal justice. In this research, we attempt to attempt to address the pivotal challenge of tradeoff between model accuracy, interpretability, explainability and specifically the effect of data bias on fairness in the autonomous decision-making process.

We propose here an integrated approach to combine the bias mitigation methods with explainable AI tools to improve model transparency without significantly compromising model accuracy. In this, we assessed the model behavior before and after applying the fairness aware learning techniques on multiple benchmark datasets like COMPAS, Adult Income, and health diagnosis records from UCI dataset repository. The results show that with a minimal loss in accuracy, we can achieve significant gains in fairness and interpretability of opaque ML models. By using various quantitative measures and pictorial representations, we show that it is possible to balance model accuracy, transparency, fairness in real world applications of ML models. This research provides both theoretical knowledge and practical suggestions for creating an ethical, accountable and transparent AI system.

***KEYWORDS** : Data bias, Explainable AI (XAI), Interpretable AI, LIME, SHaP, Transparent AI.*

INTRODUCTION

The growing use of advanced Machine Learning models is changing healthcare, criminal justice, finance, and many other fields. However, these complex models like deep neural networks often work like 'black boxes.' While they can be very accurate in their predictions, it's hard to understand how they arrive at those decisions, making it difficult to trust them completely. A related problem is data bias. If the data we feed these systems is incomplete, skewed, or reflects historical prejudices, the results can be unfair or discriminatory. This bias can creep in because of societal norms, prejudiced data collection, or even how we interpret the information.[1]. As machine learning becomes a bigger part of how decisions are made in all kinds of industries, the ethical problems caused by bias in data and algorithms are really starting to stand out [1] [2]. If we don't deal with bias in data, it can have a lot of serious consequences. It can lead to people getting wrongly approved or denied for loans, unfairness in hiring, and even problems with fairness in the criminal justice system [1]. The main problem is that we must admit it's impossible to get rid of all bias in AI that uses data. Bias is almost inevitable when dealing with data that reflects human behaviour and real-world activities [3]. Addressing it isn't as simple as flipping a switch it requires a multifaceted approach that considers technical solutions, ethical implications, and strong governance [4]. This is where Explainable AI (XAI) plays a crucial role. By making machine learning models more transparent and easier to interpret, XAI allows developers to understand how specific inputs influence the model's decisions [5]. This visibility helps identify unfair patterns or potentially discriminatory outcomes. When we better understand where bias comes from and how it impacts results and use tools like XAI to mitigate it we move closer to building AI systems that are both fair and trustworthy [6]. Tackling bias effectively also means acting at every stage of the

model's lifecycle, before it's built, while it's being trained, and even after it's deployed [7].

LITERATURE REVIEW

Based on the research we've explored, it's evident that one of the most significant challenges in machine learning is the lack of transparency in how models make decisions. Adding to this complexity is the persistent issue of data bias, which can seriously affect the fairness and reliability of the outcomes.

The aim of Explainable AI is to shape a future where AI decisions are transparent, fair, and equitable for all. Achieving this vision requires reliable methods to evaluate how effectively different strategies reduce bias, particularly in relation to clearly defined fairness objectives. [1].

A comprehensive framework lays out a well-structured approach to making machine learning models more transparent and accountable. The authors present practical methods for identifying and reducing biases within the algorithms, aiming to ensure that the outcomes of data analysis are fairer and more equitable. [2].

The research highlights that Explainable AI plays a key role in building trust in machine learning models. Techniques like identifying the most influential features and using rule-based explanations help developers uncover issues within their models. This cycle of feedback and refinement not only improves the models' accuracy but also makes them more dependable over time. [3].

Biases can emerge at various stages—from how data is collected, to the way algorithms are designed, or even by reinforcing existing societal stereotypes. For example, errors or gaps in data collection can significantly impact how well a machine learning system performs across different groups, potentially leading to unfair or inaccurate outcomes. [5].

The research [6] presents an effective approach to reducing bias by enhancing the clarity and interpretability of AI model decisions. By making these decisions more transparent, it becomes easier to identify and address potential sources of unfairness.

When evaluating model performance, it's important to look beyond overall accuracy and focus on how equitably the model performs across different demographic groups. This involves using fairness metrics such as demographic parity, equal opportunity, and predictive parity. To ensure the data truly represents the target population, strategies like stratified sampling and data augmentation can help address imbalances, especially for underrepresented groups. Additionally, applying algorithmic bias mitigation techniques while keeping intersectionality, transparency, and ongoing monitoring in mind can lead to more fair and accountable model outcomes. [7].

It's crucial to recognize that bias can creep into AI systems at any stage, right from data collection to the model's real-world deployment. Tackling bias effectively means considering the entire lifecycle of the AI system. One effective strategy is to balance the dataset, especially when some groups are underrepresented. Techniques like generating synthetic data can help ensure broader representation, allowing the model to learn from a more complete and fairer dataset, and ultimately reducing the risk of biased outcomes. [9].

To address bias in AI, pre-processing techniques are often used to improve the quality of training data essentially 'cleaning' it before it's fed into the model. This can include re-weighting samples to amplify the influence of underrepresented groups or transforming the data to reduce built-in biases. Beyond data preparation, bias can also be tackled during model training by adjusting the algorithms themselves to promote fairness. Post-processing steps further help by refining the model's outputs to ensure they meet fairness standards. Ultimately, identifying and mitigating bias is a complex task that benefits from collaboration across disciplines, including legal, AI, and ethical expertise. [11].

The research [12] advocates for a riskbased approach to ensure accountability in AI powered products. It emphasizes the need to explore the potential risks posed by AI technologies and to consider their broader societal and organizational impacts. By doing so, the study aims to establish a practical, management focused framework that organizations can integrate into every stage of their product development lifecycle.

Research work in [13] introduces a structured approach built around four essential components: the Model Impact and Clarification Framework, which promotes transparency and accountability; the Evaluation Plan Framework, which ensures proper resource allocation; the Evaluation Support Framework, designed for rigorous empirical assessment of models; and the Retraining Execution Framework, which outlines when and how models should be retrained. Together, these artefacts support effective communication among stakeholders and provide clear guidance for

evaluating and managing machine learning models in line with ethical and legal standards.

Research work discussed in [14] emphasizes the importance of adopting Explainable AI (XAI) to enhance accountability and trust in AI systems. Through a case study involving a language translation app, the study illustrates how XAI can bring greater transparency and fairness to the translation process. This real-world example highlights XAI's practical value in identifying and addressing bias, reinforcing its role in building more ethical and trustworthy AI applications.

Research article [15] presents a robust and flexible open-source framework specifically developed for the systematic, reproducible, and efficient evaluation of post hoc explanation methods. It brings together datasets, machine learning models, and evaluation metrics into a unified platform, offering an API that allows users to benchmark various explanation techniques. The framework also includes built-in implementations of feature attribution methods, along with quantitative metrics to assess the faithfulness, stability, and fairness of these explanations.

In the effort to enhance transparency in AI, a standardized documentation framework has been proposed for both training datasets and models. This framework emphasizes the need for consistent and thorough disclosure of how AI systems are created, trained, and deployed. To further support transparency, the use of impact assessments is recommended these assessments aim to evaluate the wider societal implications of AI systems, ensuring that their development and use are aligned with ethical and responsible practices [16].

To promote transparency, the framework outlined in research study [17] focuses on quantifying the influence of individual features on the target evaluation criteria (EC). It leverages the Shapley Additive Explanations (SHAP) method to interpret machine learning models, offering a clear, data-driven analysis of how each input feature contributes to the model's predictions. This approach enables a deeper understanding of the input–output relationships, supporting more transparent and accountable AI systems

Data bias in machine learning can take many forms, each posing challenges to fairness and accuracy. Sample bias occurs when the dataset doesn't accurately represent real-world conditions, while exclusion bias arises from leaving out important information. Measurement and recall bias are introduced through inconsistencies in how data is collected or labelled. Observer bias reflects the personal judgments of individuals involved in labelling data, and racial bias emerges from the unequal representation of demographic groups. Additionally, association bias can reinforce harmful societal stereotypes, embedding them into model predictions and outcomes [18].

A wide range of techniques and methodologies have been developed to address data bias throughout the machine learning pipeline. These span across three key stages: pre-processing, where data is adjusted or balanced before training; in-processing, where fairness is built directly into the learning algorithms; and post-processing, where model outputs are refined to align with fairness criteria. Together, these approaches provide a comprehensive toolkit for mitigating bias and promoting more equitable AI outcomes [19].

Pre-processing techniques aim to improve fairness by modifying the training data to ensure it is more balanced and representative of the target population. This can involve methods such as re-sampling, re-weighting, or generating synthetic data to address imbalances and reduce the influence of biased or underrepresented groups before the model is trained [20][21]. These methods are designed to correct imbalances and distortions in the data that arise from the under-representation or uneven distribution of certain demographic groups. By addressing these issues early in the pipeline, pre-processing techniques help ensure that the model learns from a more equitable and comprehensive dataset, reducing the risk of biased predictions [22]. Data re-sampling techniques, such as oversampling minority classes or under-sampling majority classes, are widely used to balance class distributions and mitigate the dominance of overrepresented groups in the training data. Another effective pre-processing method is reweighing, which assigns varying weights to training instances based on group membership. This approach enhances the influence of under-represented groups while reducing the bias introduced by over-represented ones, helping to create a more fair and inclusive learning process [19].

Conversely, in-processing methods seek to mitigate bias in the model training stage. These techniques alter the model architecture or the learning algorithm to encourage equity and lessen discrimination. Fairness-aware algorithms direct the model toward solutions that meet predetermined fairness criteria by incorporating fairness constraints or penalties into the optimization

goal. A well-known in-processing technique is adversarial debiasing, which involves training an adversarial network alongside the main model. The adversary's goal is to detect biased patterns in the model's learned features, while the main model learns to make accurate predictions without revealing those biases. Through this process, the model is encouraged to develop fairer representations by minimizing bias-related information, leading to more equitable outcomes [23]. To address disparities in model performance across different groups, fairness-aware regularization techniques introduce penalty terms into the loss function during training. These penalties discourage the model from making biased predictions by directly accounting for fairness in the optimization process. After training, post-processing techniques are applied to refine the model's predictions. These methods adjust the outputs to meet defined fairness criteria such as equal opportunity or demographic parity without changing the underlying model, making them especially useful when modifying the model is not feasible [24].

RESEARCH METHODOLOGY

To address the trade-off between interpretability and accuracy in complex machine learning models, this study adopts a mixed-methods approach, combining both qualitative and quantitative research methodologies.

Qualitative Approach

To understand the current strategies and challenges in balancing model accuracy, interpretability, and bias mitigation, the qualitative component of this study involves an in-depth literature review. Additionally, case study analyses and expert interviews are conducted to gain insights into real-world constraints and practical implementations, offering a grounded perspective on how these trade-offs are managed in practice

Quantitative Approach

The quantitative component of this study involves conducting machine learning experiments on imbalanced or skewed datasets to perform empirical analysis. After applying various bias mitigation strategies, changes in model performance are evaluated in terms of accuracy, interpretability, and fairness. These improvements are then assessed using statistical tests and comparative analyses to determine the effectiveness of each approach.

- Mixed-Method Justification:

By integrating qualitative insights with quantitative evidence, the study offers a comprehensive understanding of the challenges at hand and strengthens the validation of proposed solutions. This combined approach ensures that both theoretical perspectives and practical outcomes are considered, leading to more robust and actionable findings.

A) Data Collection

To ensure a comprehensive analysis, we have used both public and synthetic datasets which are known to exhibit bias.

- Public Datasets

Widely used benchmark datasets such as COMPAS (criminal justice), Adult Income (socioeconomic bias), and Medical Diagnosis (healthcare bias) are employed to study the presence and impact of bias in real-world data. These datasets are specifically chosen for their relevance to high stakes decision-making contexts, where fairness, accountability, and accuracy are critically important.

- Synthetic Datasets

Synthetic datasets are generated to simulate controlled scenarios of bias, enabling precise analysis of specific types of discrimination, such as gender or racial bias. By carefully manipulating data distributions, synthetic data allows researchers to isolate the effects of bias and assess model performance under different levels of skewness and imbalance.

- Data Preprocessing

Data cleaning and normalization are carried out to ensure consistency and reliability across the dataset. Prior to model training, bias assessment is conducted using statistical tests such as Chi-square tests and disparity measures to quantify and identify any inherent biases. This step is crucial for understanding the nature and extent of bias present in the data, allowing for informed mitigation strategies to be applied effectively.

B) Model Selection

The research focuses on advanced machine learning models that typically demonstrate high accuracy but pose interpretability challenges.

Complex Models Prone to Bias

- Deep Learning Models

Though Neural networks and CNNs are highly accurate models, they are analysed due to their layered structure, which often leads to opacity.

- Ensemble Methods

Models like Random Forest and Gradient Boosting are chosen for their robustness and predictive power but also their potential to embed biases from base learners.

- Rationale for Model Choice

These models represent real-world applications where interpretability and fairness are crucial. Their inherent complexity makes them ideal for studying the accuracy-interpretability-bias trade-off.

- Baseline Models for Comparison

Simpler models, such as Decision Trees and Logistic Regression, are included as benchmarks for interpretability.

C) Evaluation Metrics

To comprehensively evaluate the models, a combination of accuracy, interpretability, and bias metrics is utilised.

- Accuracy Metrics

Accuracy, Precision, Recall, F1-Score: These metrics provide a standard assessment of predictive performance.

- Interpretability Metrics

i. Feature Importance Scores (SHAP, LIME): Quantify how individual features contribute to predictions.

ii. Model Transparency Score: An aggregated metric that combines visual interpretability and textual explanations.

- Bias Metrics

i. Demographic Parity: Measures whether different demographic groups receive similar predictions.

ii. Equal Opportunity: Assesses fairness by comparing the true positive rates across groups.

iii. Disparate Impact Ratio: Analyses whether outcomes disproportionately affect certain subgroups.

- Composite Score

A weighted metric that balances accuracy, interpretability, and fairness, providing a holistic evaluation of model performance.

D) Bias Mitigation Techniques

The study implements and compares various bias mitigation strategies to enhance both interpretability and accuracy.

- Pre-processing Techniques

i. Data Augmentation: Balancing underrepresented classes to reduce bias in training data.

ii. Reweighting: Adjusting the importance of data points based on demographic attributes.

- In-processing Techniques:

i. Fairness-Aware Algorithms: Modifying loss functions to incorporate fairness constraints (e.g., adversarial debiasing).

ii. Regularisation Techniques: Penalising unfair outcomes during model training.

- Post-processing Techniques:

i. Explanation-Based Bias Correction: Analysing model outputs using SHAP or LIME to identify biased decision patterns.

ii. Recalibration Methods: Adjusting prediction probabilities to mitigate bias without altering model structure.

E) Validation and Testing

To ensure robust findings, the proposed methods are validated through a rigorous testing process.

- Performance Before and After Bias Mitigation: The study evaluates model accuracy, interpretability, and fairness metrics before implementing mitigation strategies. After mitigation, results are compared to assess improvements.
- Cross-Validation: K-fold cross-validation is performed to ensure generalizability and reduce variance in performance estimates.
- Statistical Significance Testing: Paired t-tests are conducted to determine if observed improvements are statistically significant.
- Sensitivity Analysis: Varying levels of bias are introduced to test the robustness of the mitigation methods.

To implement and evaluate the proposed framework, a range of libraries and interpretability tools are used,

Bias Mitigation Libraries

i. FairLearn: Offers algorithms and metrics for assessing and improving fairness.

ii. AIF360 (AI Fairness 360): Provides a suite of bias detection and mitigation algorithms.

Interpretability Tools

i. SHAP (SHapley Additive exPlanations): Quantifies the contribution of each feature to model predictions.

ii. LIME (Local Interpretable Model-Agnostic Explanations): Generates interpretable approximations of complex model outputs.

Machine Learning Frameworks

Scikit-learn, TensorFlow, PyTorch: Used for building, training, and evaluating machine learning models.

Data Analysis Tools

i. Pandas and NumPy: Data manipulation and preprocessing.

ii. Matplotlib and Seaborn: Visualisation of bias metrics and model performance.

RESULTS AND ANALYSIS

Using the selected benchmark datasets, we evaluated model performance on both predictive accuracy and interpretability before and after the application of bias mitigation techniques.

The Accuracy Comparison shown in Figure 1 illustrates the change in the model accuracy before and after bias mitigation techniques are applied. Bias mitigation caused only a small reduction in accuracy (less than 1.5%) across all datasets. This slight accuracy trade-off is an acceptable cost for enhanced transparency and fairness in high-stakes domains.

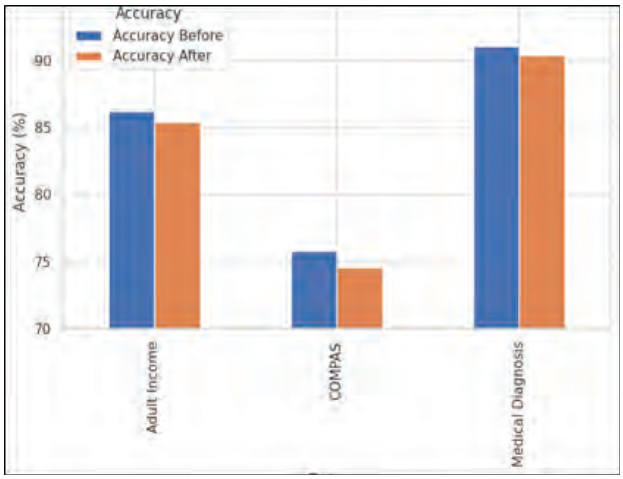

Fig. 1:Model Accuracy Before and After Bias Mitigation

The Interpretability Score Comparison shown in Figure 2illustrates the change in interpretability scores before and after Bias mitigation techniques are applied. Post-mitigation models showed a noticeable improvement in interpretability scores, especially for complex models like neural networks and ensemble methods. Medical Diagnosis models achieved near-maximum interpretability (score 5) with the integration of SHAP and LIME.

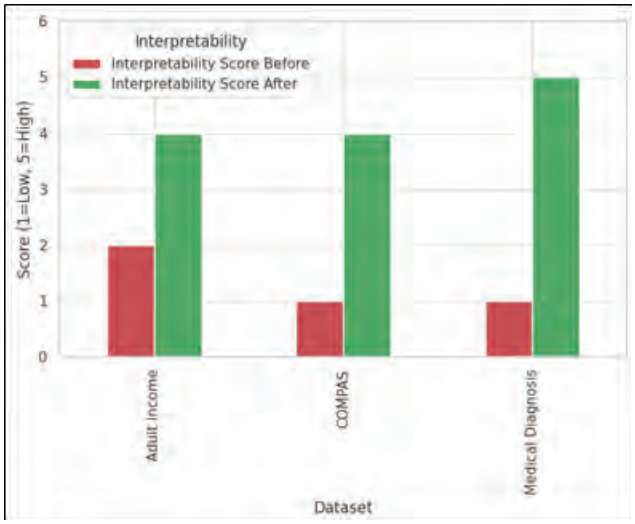

Fig. 2: Interpretability Score Before and After Bias Mitigation

Bias was quantitatively assessed using metrics like Demographic Parity Difference (DPD) and Equal Opportunity Difference (EOD). the bias metrics reduction and the comparative trade-off data obtained from the bias mitigation evaluation is presented in Table 1.

Table 1: Bias Reduction Metrics

Dataset	Metric	Bias Before	Bias After
Adult Income	DPD	0.23	0.08
COMPAS	EOD	0.29	0.12
Medical Diagnosis	DPD	0.14	0.05

These reductions indicate a 65–60% improvement in fairness metrics post-mitigation.

Table 2: Accuracy Impact

Dataset	Accuracy in % Before	Accuracy in % After	Drop %
Adult Income	85.4	84.6	0.8
COMPAS	77.2	76.0	1.2
Medical Diagnosis	91.1	90.4	0.7

Table 2 describes the loss in accuracy while we try to be fair and transparent. It is visible that Accuracy loss is minimal i.e. less than 1.5% across all datasets.

This indicates that the small performance trade-off is

acceptable given the substantial ethical and social gains

Table 3 comprehensively describes that interpretability enhancements and bias reductions are achievable with minimal impact on model accuracy.

Table 3: Comparative Analysis: Accuracy vs Interpretability vs BIAS

Dataset	Accuracy drop (%)	Bias Reduction	Interpretability Change
Adult Income	0.8	Significant	Moderate Improvement
COMPAS	1.2	High	High Improvement
Medical Diagnosis	0.7	Moderate	High Improvement

All datasets showed significant reductions in bias, particularly in group-based fairness metrics, indicating that the mitigation techniques effectively reduced unfair disparities.

DISCUSSION

This research work demonstrates a clear trade-off between accuracy, interpretability, and avoiding bias in sophisticated machine learning models. Although accurate models are generally opaque, the combination of interpretability tools such as SHAP and LIME with fairness-aware learning methods can easily minimise bias without too much sacrifice in performance. The results indicate that small reductions in accuracy can result in significant improvements in fairness and explainability. The findings highlight the moral imperative of building models that are not only accurate but also fair and understandable. Applying mitigation techniques for bias ensures that machine learning is more balanced across different groups, thus bringing machine learning practice in line with overall societal ideals like accountability, transparency, and non-discrimination. Even with promising results, reconciling high accuracy with interpretability is still the main challenge. Intricate models are difficult to simplify, and certain bias reduction techniques might create trade-offs that compromise performance. Interpretability methods can also be model- and dataset-dependent in effectiveness, reducing their applicability across diverse settings.

CONCLUSION

This research illustrates that one can enhance the transparency of sophisticated machine learning models with minimal sacrifice of accuracy. With the incorporation of interpretability tools and bias reduction methods, models can provide fairer outcomes with minor compromise on performance.

The research contributes both theoretically and practically by suggesting a structured approach to solve the accuracy-interpretability-bias trade-off. It provides a guideline for constructing more equitable, more accountable AI systems and presents actionable techniques with real–world application across fields such as healthcare, finance, and criminal justice.

FUTURE SCOPE

The future generation research would investigate hybrid approaches that couple the prognostic power of sophisticated algorithms with the clarity of lower-fidelity models. There is also a requirement for sophisticated, domain-specific bias reduction techniques and stronger interpretability frameworks. Real-world deployment studies and multilateral cooperation between technical and ethical fields will further assess and hone these methods.

REFERENCES

1. J. Angwin, J. Larson, S. Angell, L. Lum, and J. Kleinberg, “Ethical Considerations and Strategies to Mitigate Bias Problem in Machine Learning.”
2. E. Hohma, A. Boch, and R. Trauth, “Towards an Accountability Framework for Artificial Intelligence Systems.” Aug. 2022.
3. S. Leavy, B. O’Sullivan, and E. Σιαπέρα, “Data, Power and Bias in Artificial Intelligence,” arXiv (Cornell University), Jan. 2020, doi: 10.48550/arxiv.2008.07341.
4. Y. Martel and L. Noleto, “Artificial Intelligence in the financial sector: 13 key challenges of the future.”
5. T. Royal Society, “Explainable AI: the basics.” Nov. 2019.
6. R. Deokar, P. Nanjundan, and S. N. Mohanty, “Transparency in Translation: A Deep Dive into Explainable AI Techniques for Bias Mitigation,” p. 1, Jul. 2024, doi: 10.1109/apcit62007.2024.10673712.
7. K. Lloyd, “Bias Amplification in Artificial Intelligence Systems,” arXiv (Cornell University), Jan. 2018, doi: 10.48550/arxiv.1809.07842.
8. R. Srinivasan and A. Chander, “Biases in AI systems,” Communications of the ACM, vol. 64, no. 8, p. 44, Jul. 2021, doi: 10.1145/3464903.
9. E. H. Shortliffe, R. Davis, S. G. Axline, B. G. Buchanan, C. C. Green, and S. N. Cohen, “Computer-based consultations in clinical therapeutics: Explanation and

rule acquisition capabilities of the MYCIN system," Computers and Biomedical Research, vol. 8, no. 4, p. 303, Aug. 1975, doi: 10.1016/0010-4809(75)90009-9.

10. R. Srinivasan and A. Chander, "Biases in AI Systems," Queue, vol. 19, no. 2, p. 45, Apr. 2021, doi: 10.1145/3466132.3466134.

11. T. Araujo, N. Helberger, S. Kruikemeier, and C. H. de Vreese, "In AI we trust? Perceptions about automated decision-making by artificial intelligence," AI & Society, vol. 35, no. 3, p. 611, Jan. 2020, doi: 10.1007/s00146-019-00931-w.

12. E. Hohma, A. Boch, and R. Trauth, "Towards an Accountability Framework for Artificial Intelligence Systems." Aug. 2022

13. P. R. Nagbøl and O. Müller, "X-RAI: A Framework for the Transparent, Responsible, and Accurate Use of Machine Learning in the Public Sector.," p. 259, Jan. 2020, Accessed: Feb. 2025. http://ceur-ws.org/Vol-2797/paper25.pdf

14. Md. T. HOSAİN, M. H. ANİK, S. Rafi, R. TABASSUM, K. INSİA, and Md. M. SIDDIKY, "Path To Gain Functional Transparency In Artificial Intelligence With Meaningful Explainability," Journal of Metaverse, vol. 3, no. 2, p. 166, Oct. 2023, doi: 10.57019/jmv.1306685.

15. C. Agarwal et al., "OpenXAI: Towards a Transparent Evaluation of Model Explanations," arXiv (Cornell University), Jan. 2022, doi: 10.48550/arxiv.2206.11104.

16. B. Mittelstadt, "Interpretability and Transparency in Artificial Intelligence," in Oxford University Press eBooks, Oxford University Press, 2022, p. 378. doi: 10.1093/oxfordhb/9780198857815.013.20.

17. H. Eskandari, H. Saadatmand, M. Ramzan, and M. Mousapour, "Innovative framework for accurate and transparent forecasting of energy consumption: A fusion of feature selection and interpretable machine learning," Applied Energy, vol. 366, p. 123314, Apr. 2024, doi: 10.1016/j.apenergy.2024.123314.

18. Seven types of Data-Bias in Machine Learning (April, 6, 2023) Retrieved from https://www.telusdigital.com/insights/ai-data/article/7-types-of-data-bias-in-machine-learning

19. J. Angwin, J. Larson, S. Angell, L. Lum, and J. Kleinberg, "Ethical Considerations and Strategies to Mitigate Bias Problem in Machine Learning."

20. Q. Bamboat and H. Q. Yu, "Literature Study on Bias and Fairness in Machine Learning Systems," p. 1960, Nov. 2023, doi: 10.1109/trustcom60117.2023.00267.

21. H. Lamba, K. T. Rodolfa, and R. Ghani, "An Empirical Comparison of Bias Reduction Methods on Real-World Problems in High-Stakes Policy Settings," ACM SIGKDD Explorations Newsletter, vol. 23, no. 1, p. 69, May 2021, doi: 10.1145/3468507.3468518.

22. J. M. Cock, M. Bilal, R. L. Davis, M. Marras, and T. Käser, "Protected Attributes Tell Us Who, Behavior Tells Us How: A Comparison of Demographic and Behavioral Oversampling for Fair Student Success Modeling," p. 488, Feb. 2023, doi: 10.1145/3576050.3576149.

23. P. Linardatos, V. Papastefanopoulos, and S. Kotsiantis, "Explainable AI: A Review of Machine Learning Interpretability Methods," Entropy, vol. 23, no. 1. Multidisciplinary Digital Publishing Institute, p. 18, Dec. 25, 2020. doi: 10.3390/e23010018

24. A. Mishler, E. H. Kennedy, and A. Chouldechova, "Fairness in Risk Assessment Instruments," p. 386, Feb. 2021, doi: 10.1145/3442188.3445902.

Efficient Cloud Based System for BCI Signal Analysis

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ABSTRACT

Brain-computer interfaces (BCIs) signify a transformative shift in human-computer interaction and moving from laboratory environments to real-world environments. This comprehensive study looks at how BCI and cloud-based infrastructures can be integrated and work together to achieve real-time signal analysis in field environment. In cloud based BCI applications channel selection and virtual machine (VM) provisioning methods are crucial for managing computational complexity, real-time performance and optimizing cloud computing resources. To meet the above challenges, our research focuses on adaptive EEG channel selection using Greedy Localization Technique (GLT) to get optimum channel selection and proposed an autoscaling framework (ACF) for VM provisioning to reduce delay at cloud service provider (CSP) end. We provide efficient solutions to deal with channel selection, offloading decisions, network unpredictability, energy optimization, and resource management for BCI motor imagery (MI) applications. Our results signify the reduction in offloading data size up to 87.5% using GLT without compromising accuracy level. This research provides a multifaceted approach to make reliable, scalable BCI systems that can be used in a real-time environment.

KEYWORDS *: Hybrid BCI, Real time BCI, Cloud based BCI, Computation offloading, Autoscaling framework.*

INTRODUCTION

Brain-computer interfaces (BCI) are revolutionary innovations that connect human imagery thoughts with digital technology. The main idea behind BCI is that they can read neural signals, especially electroencephalogram (EEG) data, and turn these neural signals into commands that may be used to control and generate appropriate action. BCI scope is not limited to medical field, it has effects in many areas, such as cognitive monitoring, healthcare rehabilitation, assistive technologies, survey, BCI gaming and entertainment [1]. Early BCI systems were mostly used in labs since they needed a lot of computing power for a multimodal or hybrid signal data acquisition and controlled circumstances to work best [2]. In today's era there is a growing need for practical, real-world uses, portable, and efficient BCI systems that can work in a different field environment [3], [4]. One of the main problems with modern BCI research is finding a way to balance the need for complex computations with real-time signal analysis support while making sure the system works reliably in a range of different environment scenarios as we are getting challenges in robotics field to operate in multiple environments [5]. The evolution of cloud computing models gives us new ways to solve these problems through distributed processing, flexible resource allocation, and adaptive workload management. By using cloud infrastructure, BCI systems can move complex computing activities to the cloud while still being able to process data locally for tasks that need to be done quickly. This mixed approach makes it possible to create advanced BCI applications that can handle different network conditions and processing needs. Cloud based BCI system has many advantages over standalone ones [6]. The scalability and elasticity feature of cloud architecture dynamically allocates computational resources to meet real-time signal analysis [6]. The distributed processing capability of cloud-based systems allows complex distributed processing methodologies to perform BCI

pipeline components on numerous nodes. This distribution supports concurrent EEG signal processing, feature extraction, and collaborative categorization. The cost-effective resource management is an important feature of cloud based BCI; Traditional BCI systems demand large computational hardware investments whereas cloud techniques turn capital expenditures into operational costs, enabling more flexible resource management and lower BCI implementation hurdles. However, cloud-based BCI systems present new latency, security, privacy, and network dependency issues. These problems require systematic architecture, data flow optimization, and intelligent provisioning strategies to optimize performance across varied deployment situations [7]. Channel optimization and virtual machine provisioning are important constraints in cloud based BCI. Channel optimization is required to reduce data size whereas VM provision includes over-provisioning and under-provisioning issues. Over provisioning specifies wastage of resources and increases in cost factors for cloud service provider whereas under provisioning results in scarcity of resources and non-availability of VM to BCI application module [8], [9].

Traditional VM provisioning approaches often follow static strategies where resources are allocated in response to threshold rule i.e., VM availability is maintained with threshold limit i.e., according to workload condition (70%0 – 30 % utilization ratio). Researchers also preferred trade off based VM availability like service cost and waiting cost [10]. However, BCI applications to meet real time signal analysis require proactive provisioning strategies that anticipate computational requirements based on signal characteristics, user patterns, and environmental conditions. Different stages of the processing pipeline may have varying computational requirements, memory demands, and latency constraints therefore we have provided efficient provisioning strategies that consider these heterogeneous requirements while maintaining cost efficiency and resource utilization optimization [11], [12]. We have proposed an autoscaling framework that helps minimize delays cost, energy efficiency and ensure VM availability during real-time operations. This comprehensive research addresses the integration of BCI technology, cloud computing, and intelligent resource management through several key contributions:

- Novel approach combining spatial, spectral, functional, and graph-based features with deep learning-derived importance measures for robust channel selection in situations of different network environments.
- Development of the Greedy Localization Technique (GLT) that combines data-driven and model-driven feature extraction for optimal EEG channel selection in field environments.
- Using COSMOS model for making computational offloading decisions based on multi-parameter optimization – inference time, energy, and cost factors.
- Proposed autoscaling framework specifically tailored for BCI workloads to meet real time signal analysis.

Table 1 Abbreviation

BCI	Brain Computer Interface
ACF	Autoscaling Framework
VM	Virtual Machine
EEG	Electroencephalogram
MI	Motor Imagery
GLT	Greedy Localization Technique
COSMOS	Computation Offloading Strategy Model for Optimized System
MST	Minimum Spanning Tree
MCC	Matthews Correlation Coefficient
QoS	Quality of Services

METHODOLOGY

Our proposed system architecture integrates cloud-based BCI processing capabilities to create a comprehensive BCI platform optimized for real-world deployment. The architecture consists of several interconnected components that work together to provide adaptive, efficient, and robust neural signal processing capabilities.

Dataset and Experimental Setup

Our research uses the comprehensive EEG Motor Movement/Imagery Database from PhysioNet [32], which provides standardized motor imagery dataset suitable for BCI algorithm development and evaluation. The dataset contains recordings from 109 volunteers who performed motor imagery tasks in laboratory conditions. Total 19 subjects selected from the dataset for balanced representation with 64 EEG channel using the international 10-20 electrode placement system and 250 Hz sampling rate. The task is defined as four distinct motor imagery classes (Left fist imagination, Right fist imagination, Both fists imagination, Both feet imagination). The raw EEG data undergoes basic preprocessing to enhance signal quality and remove artifacts: Bandpass filtering: 4-30 Hz

frequency range to focus on motor-related rhythms and Notch filtering: 50/60 Hz powerline interference removal.

Data Driven Feature Selection

Our data-driven feature extraction approach combines multiple complementary feature types to create a comprehensive representation of EEG channel importance and relevance for motor imagery classification.

Spatial features

Spatial features capture the topographical distribution of neural activity across the scalp, providing insights into the anatomical sources of motor imagery signals. The spatial analysis considers electrode positions and their geometric relationships. The spatial distance matrix is normalized to enable comparison across different electrode configurations.

$$D_{ij} = distance(pos_i, pos_j) \quad (1)$$

Functional connectivity features

Functional connectivity measures reveal how different brain regions communicate during motor imagery tasks. We compute correlation-based connectivity measures that capture both linear and nonlinear relationships. The functional connectivity matrix undergoes normalization to ensure consistent scaling.

$$C_{ij} = |Corr\,(data_i, data_j)| \quad (2)$$

The integration of spatial and functional information creates a comprehensive channel relationship matrix. This formulation balances spatial proximity with functional connectivity, where channels that are spatially close but functionally dissimilar (or vice versa) receive intermediate importance scores.

Graph Feature

Graph theoretical methods provide powerful tools for analyzing the complex network structure of EEG connectivity patterns. We employ minimum spanning tree (MST) algorithms to identify the most critical connections in the brain network. Node degree calculation in the MST:

$$Degree(v_i) = \sum_j m_{ij} \quad (3)$$

Spectral Feature

Spectral features capture the frequency domain characteristics of EEG signals, which are particularly relevant for motor imagery tasks due to the distinct spectral patterns associated with motor-related brain rhythms. Power Spectral Density (PSD) Estimation using Welch's Method to calculate individual channel importance score.

$$PSD\,(f) = \frac{1}{N}\sum_{k=1}^{N}|\dot{X}_k(f)|^2 \quad (4)$$

The final channel importance score combines spectral and graph-based measures.

$$Combined\ importance(v_i) = \frac{Node\ Degree\ norm(v_i) + PSD\ norm(v_i)}{2} \quad (5)$$

$$Selected\ indices = \{i: Combined\ importance(v_i) > Threshold \quad (6)$$

The threshold for channel selection adapts based on the distribution of importance scores:

Threshold = mean (Combined_Importance) + k × std (Combined_Importance) (7)

Where k is an adaptive scaling factor that adjusts based on Signal quality metrics

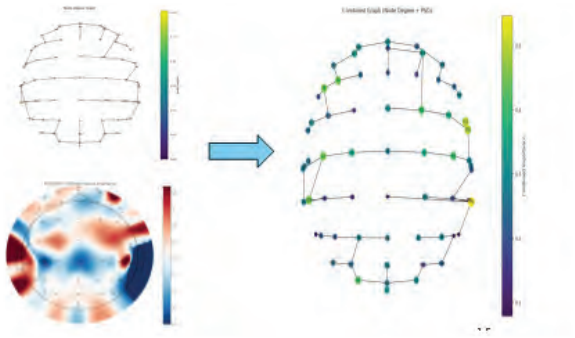

Fig. 1: Combined Feature importance using hybrid features

Selected_Channels = {i: Combined_Importance(v_i) > Threshold} (8)

This selection process as shown in Figure 1 ensures that only the most informative channels are retained for subsequent processing stages.

Model-Driven Feature Selection

Model-driven feature extraction leverages deep learning architectures to automatically discover channel importance patterns that may not be apparent through traditional signal processing methods. Our approach employs convolutional neural networks (CNNs) specifically designed for EEG signal analysis.

Table 2: Convolutional Neural Network

Layer (type)	Output Shape	Parameter
conv1d (Conv1D)	(None, 250, 32)	6,176
max_pooling1d	(None, 125, 32)	0
conv1d_1 (Conv1D)	(None, 125, 64)	6,208
max_pooling1d	(None, 62, 64)	0
flatten (Flatten)	(None, 3968)	0
dense (Dense)	(None, 128)	508,032
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 2)	258

The combination of data-driven and model-based aspects built an exhaustive description of channel salience that traded off explicit signal features against learned classification importance.

Greedy Localization Technique (GLT)

The Greedy Localization Technique (GLT) represents an innovative approach to adaptive channel selection that balances exploration and exploitation in the feature selection process. Unlike traditional feature selection methods that rely on static criteria, GLT dynamically adapts its selection strategy based on real-time performance feedback and resource constraints. GLT is based on the principle of local optimization with global awareness. At each iteration, the algorithm makes locally optimal decisions while maintaining knowledge of global performance trends [33]. This approach is particularly well-suited for BCI applications where:

- Real-time constraints limit the computational budget for feature selection
- Signal characteristics may change over time requiring adaptive strategies
- Resource availability varies based on network conditions and device capabilities
- Performance requirements may change based on application context

The adaptive keep ratio mechanism forms the core of GLT's dynamic behavior, allowing the algorithm to adjust its aggressiveness in channel reduction based on performance feedback. The performance metrics for evaluation and validation are as follows:

Classification Accuracy: Overall correctness of motor imagery classification

Matthews Correlation Coefficient (MCC): Balanced performance measure accounting for class imbalance

Root Mean Square Error (RMSE): Prediction error magnitude

Resource Utilization: Computational power and energy consumption metrics

Computation offloading: Data size and bandwidth availability

The keep ratio adaptation considers multiple performance metrics:

Weighted _score = (weights['accuracy'] * accuracy + weights['mcc'] * mcc +weights['rmse'] * normalized_rmse) / sum(weights.values()) (9)

Proposed GLT Algorithm

Procedure GLT Algorithm*(channel_mask, keep_ratio, weighted score)*

1. *Channel_mask = feature_importance(Data_driven+Model driven feature)*
2. *Combined_importance = (importance + channel_importance[channel_mask]) / 2*
3. Set *Keep_ratio= 0.9*
4. *Calculate a weighted score based on dataset characteristics and update the keep ratio*
   *Weighted_score = (weights['accuracy'] * accuracy + weights['mcc'] * mcc + weights['rmse'] * normalized_rmse) / sum(weights.values())*
5. *Adapt the rate of channel reduction based on model's performance. If performance improves significantly (>5%), the keep ratio increases, slowing down channel reduction.*
   if weighted_score > best_weighted_score:
   best_weighted_score = weighted_score
   best_mask = channel_mask.copy()
6. *if weighted_score > previous_weighted_score * 1.05:*
   *keep_ratio = min (keep_ratio * 1.1, 0.95)*
   *else: keep_ratio = max (keep_ratio * 0.9, 0.5)*
   previous_weighted_score = weighted_score
   *num_to_keep = max(int(np.sum(channel_mask) * keep_ratio), min_channels)*
8. *set the threshold value for channel importance, determining which channels to keep.*
   a. *Threshold= np.sort(combined_importance)[-num_to_keep] and update channel_mask*
9. *Repeat steps (5) – (8) until a stopping condition is met (e.g., minimum number of features reached or performance threshold met).*
10. **End Procedure**

Cosmos: Computation Offloading Strategy Model for Optimized System

The computation offloading strategy model for optimized systems simulates field conditions and predicts offloading decisions, focusing on local energy consumption, data size requirements, cost, and inference time. Weighted parameters for decision-making are defined in Table 3.

These weights are utilized in the cosmos decision function as follows:

$$local_{score} = \alpha * local_{time} + \beta * local_{energy} + \gamma * local_{cost} (10)$$

$$cloud_{score} = \alpha * cloud_{time} + \beta * cloud_{energy} + \gamma * cloud_{Cost} (11)$$

Table 3 Cosmos Model parameter

$\alpha = 0.5$ (for time consideration)	Transfer time = data_size / network_bandwidth
$\beta = 0.3$ (for energy consideration)	Computation time = local $_{time}$ / cloud_computing_power
$\gamma = 0.2$ (for cost consideration)	Cloud $_{time}$ = Transfer_time + cloud_compute_time
base_network_bandwidth= 3 Mbps	Cloud $_{energy}$ = local $_{energy}$ / cloud_energy_efficiency
bandwidth_variation = 0.5	local_cost = 0
cloud_computing_power = 100	Cloud $_{Cost}$ = cloud_cost_per_second * cloud_time
cloud_energy_efficiency = 5	Local $_{energy}$ = inference_time * (0.8, 1.2)

Computation offloading is beneficial if cloudscore is less than localscore else local execution will be used. Here's how they affect the decision:

Time Factor: It is the ratio of the processing time locally with respect to the total data transfer and cloud processing time:

α * local time vs α * cloud time (12)

Energy Factor: It is the comparison of local processing energy usage with the energy efficiency of cloud processing:

β * local energy vs β * cloud energy (13)

Cost Factor: It is the comparison of the cost of local processing (usually taken as 0) with the cost of utilizing cloud resources:

γ * local cost vs γ * cloud cost (14)

The scope of these parameters can balance multiple objectives. By adjusting these weights, we can assign different priorities according to the specific needs of the EEG analysis task and environmental conditions. We can assign flexibility to different scenarios e.g., for time-critical applications, α can be assigned higher and in power-limited environments, β can be assigned higher priority. For cost consideration or long-term deployments, γ can be assigned higher. These parameters are adjustable based on data size or specific BCI application deployment needs and thus the system is made field scenario variable, providing design flexibility in the field environment. It's a comprehensive approach to handling resources by simultaneously considering time, energy, and cost, the model gives more holistic means for resource management of field environment BCI systems. In the context of our EEG analysis pipeline, these parameters allow COSMOS to make subtle computation offloading decisions. EEG signal processing is non-linear and computation-intensive, and environments tend to have constraints on power, computing resources, and network connectivity. That's why with careful consideration of α, β, and γ parameters as per network and operating conditions availability, we can optimize our EEG analysis system's resource utilization, processing rates, energy usage, and long-term operational costs. It leads to a more robust and feasible solution for real-world EEG analysis applications. The key terminology of offloading is given in Table 3.

Virtual Machine Provisioning Strategies

The proposed Auto-Scaling Framework (ACF) (Y. Kumar et al., 2023) is founded on the MAPE-K (Monitor, Analyze, Plan, Execute over a common Knowledge base) pattern (Y. Kumar et al., 2023) and provides a formal approach to cloud resource management for BCI applications. The architecture makes a distinction between four main components in which the system runs within given clock times, providing a closed loop of feedback:

Monitor: Pulls performance BCI data and system state data

Analyze: Monitors processes to estimate system parameters and predict future BCI workloads

Plan: Assigns appropriate resources based on analysis results and QoS requirements

Execute: Carries out resource allocation decisions by scheduling tasks and managing VMs

All of these components share a common Knowledge base with historical data, performance models, and config parameters. To formalize the cloud based BCI resource management issue, we model the cloud service provider as

an M/M/s queuing system, where the arrival of BCI tasks is modeled by a Poisson distribution with arrival rate λ and the service time by an exponential distribution with service rate μ. The system utilizes 's' identical virtual machines as servers and processes jobs in first-come, first-served order. The fundamental objective is to maintain VM provisioning according to the SLA-agreed QoS guarantee level for zero delay (α), expressed as:

$$1 - W_q(0) \leq \alpha \quad (15)$$

where $W_q(0)$ refers to the zero wait time probability on CSP side. The planning component implements the core auto-scaling algorithm, which determines the optimal number of VM instances based on predicted BCI workload and QoS requirements. In this phase, the proposed auto-scaling mechanism is used for updating the number of running VMs as per SLA negotiated QoS assurance level (α) for availability. The pseudo-code for this scaling mechanism is depicted in given ACF algorithm. Inputs to this algorithm are predicted task arrival rate (λp(t+1)), mean service rate (α), the number of running VM instances, and required QoS assurance level (α).

Proposed Auto Scaling Algorithm (ACF)

1 procedure Instance_estimator (λt+1,p , μ, s, α)
2 temp = s; //running VMs
3 compute traffic intensity ρ = λt+1p /sμ
4 if (ρ > 1)
5 then increase VMs until (ρ < 1)
6 else s = s/2;
7 if(ρ > 1)
8 then increase VMs until (ρ < 1)
9 endif
10 end else
11 Compute Z = 1 −Wq(0)
12 if (α < Z) then
13 while (α < Z) do
14 s++;
15 Compute Z = 1 −Wq(0)
16 end while
17 end if
18 if (s > temp) then
19 start (s – temp) VMs;
20 end if
21 else
22 annotate (temp – s) VMs as hibernated.
23 stop(temp – s) VMs when leasing time quantum completing
24 end else
25 end procedure

The above algorithm computes the traffic intensity and checks whether the system is stable. If the system is unstable, it increases the VMs count until traffic intensity is less than 1. If the system is already stable, it decreases the VMs count to half and stabilizes the system again. This alternate phase is defined to check whether the VMs requirement has decreased for the current clock interval and further computes the QoS assurance level with the stabilized VMs count. If the QoS requirement is not met with the stabilized system VMs, it increases the VMs count until the required QoS requirements are met. Subsequently, it checks whether the new VMs requirement is higher than the existing VMs, then places an order to start new VMs. If the available VMs are higher, it first annotates the surplus VMs as hibernated and does not immediately stop them. However, if the leasing time quantum of a hibernated VM is nearing completion, it proceeds to shut down the surplus VMs. This method guarantees that the system can provide the level of required QoS for BCI applications without invoking unnecessary VM startup/shutdown processes, which may cause considerable delays.

Proposed Scheduler Algorithm

1 procedure SCHEDULER (Task t, vmslist)
2 boolean VMAvailable = false;
3 Search for a free non-hibernated VM and allocate it
4 setVMAvailable = true;
5 else if (VMAvailable == false)
6 Draw a hibernated VM with the highest remaining leasing time quanta and allocate it
7 set VMAvailable = true;
8 end else if
9 else
10 pending List.addLast(t);
11 end else
12 end procedure

The Execution module executes the VM scheduling algorithm, which allocates BCI tasks to available VMs in an intelligent manner while maximizing resource usage.

Rather than immediately shutting down the surplus VMs, ACF provides an innovative scheduler for optimizing VMs leasing time quanta. Pseudo-code of the scheduler algorithm is given in proposed scheduler algorithm. If a hibernated VM is required in the system, it withdraws the VM with maximum remaining leasing time quanta.

This one is resource utilization arrangement that aids in the identification of VMs that need to be shut down because only hibernated VMs need to be shut down. Furthermore, it also avoids the continuous profiling of leasing time quanta of the surplus VMs. The significant features are:

- Pre-emptive allocation to non-hibernated VMs for maximum usage of active resources
- On all non-hibernated VMs being occupied, selectively hibernating VMs with the highest remaining lease duration
- Shutting down hibernated VMs only when their leasing time quantum is about to expire.

This novel scheduling method bypasses the necessity to cancel in-progress tasks or move them from one VM to another, which is especially disruptive for BCI applications requiring real-time processing. One of the main features of the framework presented here is its coupling with the channel optimization methods, i.e., proposed GLT algorithm. Using efficient channel optimization that defines network aware channel selection and combining optimal cloud resource provisioning, the system defines an end-to-end solution for a cloud based BCI applications to meet real time BCI. such integration can be implemented through a number of procedures:

Workload Characterization: Channel optimization influences the computational load of BCI tasks directly by minimizing data dimensionality. The monitor component identifies these effects by monitoring execution time and enabling the system to adjust VM provisioning accordingly.

Energy Efficiency Optimization: By keeping both data transmission demands using channel optimization and queuing delays through efficient resource provisioning, the combined approach optimizes the energy efficiency gains of computation offloading. It also helps in decision making whether to offload or perform local computation in field environment.

QoS Management: The integrated strategy also guarantees QoS demand at both the data processing stage through proper classification in the face of limited channels and the resource administration stage using queuing delays.

Adaptive Resource Allocation: With channel optimization parameters improving as signal features and user needs change, the auto-scaling platform adjusts VM provisioning to ensure peak performance.

This proposed solution tackles the end-to-end optimization problem for cloud-based BCI applications, from early data acquisition to channel selection, cloud resource management, and task execution.

RESULTS AND ANALYSIS

The proposed GLT framework with VM autoscaling algorithm demonstrated significant improvements across multiple performance dimensions. The comprehensive evaluation reveals the effectiveness of our integrated approach to BCI channel selection and cloud resource management with relatively balanced classes and optimized weighting scheme (accuracy: 0.40, MCC: 0.30, RMSE: 0.30). The preliminary channel selection process through combined feature approach reduced the dataset from 64 to 10 channels before entering the iterative optimization phase. Further the channel are optimized as per network availability with resource provisioning to reduce delay.

Channel Reduction and Classification Performance

The channel reduction process achieved optimal performance with substantial computational savings through an iterative optimization process. The result signifies 10-channel configuration (F1, FCz, FC2, FC6, T7, C3, C1, Cz, CP5, CP3) achieved from comprehensive primarily feature selection from data driven and model driven approach. The iterative process using adaptive keep ratios, beginning with 0.85 in iteration 1 and stabilizing at 0.95 for subsequent iterations. The perfromance_score metric achieved its peak performance of 0.7484 at iteration 3 with 8 channels (F1, FC2, FC6, C3, C1, Cz, CP5, CP3), which was selected as the optimal configuration. Figure 2 depicts the accuracy metric, shows the efficacy of our approach during channel reduction and achieves its highest value of 0.7919 (79.19%) at iterations 3 and 5, while maintaining a strong performance above 0.75 throughout most iterations. The second metric MCC scores also ranged from 0.6708 to 0.7240, with the optimal configuration achieving 0.7240, indicating excellent classification discrimination. The channels are further eliminated by 20%, from 10 to 8 and improved overall performance in data size while maintaining accuracy.

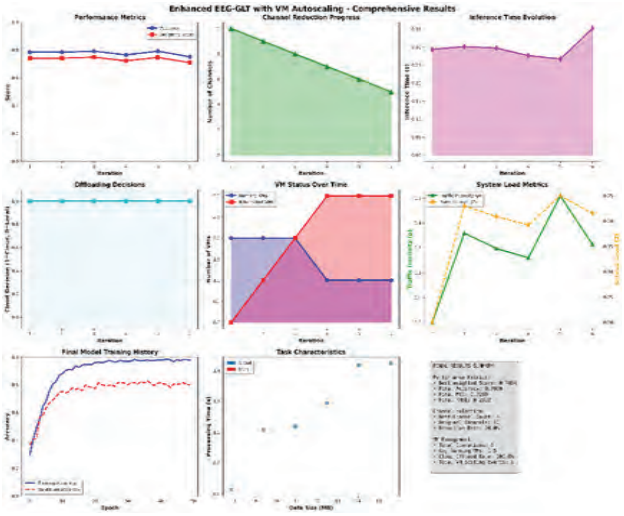

Fig. 2: Result Summary - performance metrics,VM status and accuracy

Inference Time Optimization

Real-time performance improvements were evident throughout the optimization process. The result shows that our system achieved progressive reduction in processing latency, starting from 0.2808 seconds in iteration 1 and reaching an optimal 0.2586 seconds in the final iteration, representing an 8.6% improvement in response time. The result shows significant improvement achieved between iterations 1 and 3, where inference time dropped from 0.2808s to 0.2639s, coinciding with the achievement of the best weighted score. The result showed consistent improvement as the channel count decreased: 0.2808s (10 channels), 0.2769s (9 channels), 0.2639s (8 channels), with slight variations in later iterations. For a BCI applications where millisecond-level delays can impact user experience and real-time BCI response, such performance enhancement can make great help to meet real time objective and efficient resource utilization.

VM Autoscaling and Resource Management

The proposed autoscaling framework (ACF) provides efficient solutions in maintaining Quality of service (QoS) while optimizing VM provisioning and resource utilization. Initially the system starts with 3 VMs and employs autoscaling algorithms based on traffic intensity (ρ), service level (z), and arrival rate (λ) parameters. The ACF utilized queuing theory principles with service rate μ=2.00 and reliability threshold α=0.9. The result shows dynamic scaling behavior that is evident throughout the process: iteration 1 triggered scale-up operations starting additional VMs (VM_3 and VM_0), while subsequent iterations demonstrated intelligent scale-down decisions. By iteration 4, our system optimally scaled down to 1 running VM with 3 hibernated VMs and shows it is achieving significant cost savings without any performance degradation and compromise. The traffic intensity varied from 0.000 (iteration 1) to 0.509 (iteration 5), and the system effectively managing peak loads without service degradation. The offloading decisions results show that cloud deployment is favored across all iterations and indicating optimal load distribution. The dynamically BCI tasks assigned to available VMs (VM_0, VM_1, VM_2) in early iterations, transitioning to pending task queues as optimization progressed. Such behavior demonstrates that the proposed system's efficiently balance resource efficiency with performance requirements.

System Load Balancing and QoS Metrics

The system load metrics demonstrate effective traffic management and service level optimization. Traffic intensity exhibited controlled variation, ranging from 0.0 to 0.5, with the system successfully managing peak loads around iteration 4 (0.5 intensity). Service Level 2 metrics showed complementary behavior, starting at 0.0 and reaching 0.25 at peak performance periods, indicating effective load distribution across service tiers. Figure 2 represents the correlation between traffic intensity and service levels and suggests that our autoscaling (ACF) algorithm successfully anticipated and responded to BCI nonlinear and dynamic computational demands, maintaining quality of service even during high-traffic periods.

Task Characteristics and Scalability Analysis

The result shows the efficacy of proposed system in the BCI motor imagery task analysis across different data sizes (8-14 MB) along with processing times (0.6-1.5 seconds). The scatter plot reveals that the proposed solution handles varying computational loads effectively, with processing times scaling reasonably with data size. The result shows that it can accommodate different BCI task complexities while maintaining consistent performance. The proposed VM management statistics demonstrate effective resource utilization across 6 optimization iterations, with intelligent scaling from 3 initial VMs to 1 running VM with 3 hibernated instances. It successfully balanced computational efficiency with QoS requirements and achieved optimal BCI signal processing which is primarily a requirement for cloud based BCI system. The parameters are consistently maintaining service reliability above the

0.9 threshold, with traffic intensities ranging from 0.000 to 0.509 and demonstrating robust performance of our system under varying computational loads.

These results demonstrate that integrated approach successfully addresses the critical challenges of BCI channel optimization to reduce data size and transmission time along with cloud resource management to provide a practical solution for scalable BCI systems that maintain quality of service while minimizing computational overhead and operational costs. The energy savings level (34%) achieved in our stable network environment validates the effectiveness of intelligent offloading decisions. However, 145% increase in local battery usage during a unstable conditions highlight the importance of network reliability for energy-efficient operation.

CONCLUSION

This comprehensive research demonstrates the significant potential of cloud-based brain-computer interface systems enhanced with adaptive virtual machine provisioning strategies. The proposed GLT for adaptive channel selection and the COSMOS provide effective solutions for managing the computational complexity and resource requirements of real-world BCI deployments. The key contribution and achievement for proposed methodology are first, GLT successfully reduces EEG channel requirements by 12.5% while maintaining 80% of classification performance, demonstrating an effective balance between computational efficiency and accuracy. Second an intelligent offloading, where COSMOS provides robust decision-making for computational task distribution, achieving 34% energy savings in stable network conditions while maintaining high classification accuracy. Third, provide advanced provisioning strategies which outperform traditional approaches with up to 80 % classification accuracy and appropriate system availability. Fourth comprehensive evaluation across multiple network scenarios validates system robustness and adaptability for real-world deployment conditions. The research provides a foundation for developing scalable, cost-effective, and robust BCI systems suitable for diverse applications including healthcare, assistive technology, and human-computer interaction. This work advances the state-of-the-art in cloud-based BCI systems by addressing critical challenges in computational offloading and resource provisioning. The convergence of brain-computer interfaces with cloud computing and advanced provisioning strategies opens new possibilities for ubiquitous neural interfaces that can adapt to diverse deployment scenarios while maintaining high performance and cost efficiency. As network infrastructure continues to improve and edge computing capabilities expand, cloud-based BCI systems will become increasingly viable for widespread deployment.

REFERENCES

1. R. L. Queiroz, I. Bichara De Azeredo Coutinho, G. B. Xexeo, P. Machado Vieira Lima, and F. F. Sampaio, “Playing with Robots Using Your Brain,” Brazilian Symp. Games Digit. Entertain. SBGAMES, vol. 2018-Novem, pp. 197–204, 2019, doi: 10.1109/SBGAMES.2018.00031.
2. Z. Juhasz, “Quantitative cost comparison of on-premise and cloud infrastructure based EEG data processing,” Cluster Comput., vol. 24, no. 2, pp. 625–641, 2021, doi: 10.1007/s10586-020-03141-y.
3. J. Minguillon, E. Perez, M. A. Lopez-Gordo, F. Pelayo, and M. J. Sanchez-Carrion, “Portable system for real-time detection of stress level,” Sensors (Switzerland), vol. 18, no. 8, pp. 1–15, 2018, doi: 10.3390/s18082504.
4. M. Mahmood et al., “Fully portable and wireless universal brain–machine interfaces enabled by flexible scalp electronics and deep learning algorithm,” Nat. Mach. Intell., vol. 1, no. 9, pp. 412–422, 2019, doi: 10.1038/s42256-019-0091-7.
5. P. F. Diez, V. A. Mut, E. Laciar, and E. M. A. Perona, “Mobile robot navigation with a self-paced brain-computer interface based on high-frequency SSVEP,” Robotica, vol. 32, no. 5, pp. 695–709, 2014, doi: 10.1017/S0263574713001021.
6. M. C. Thompson, “Critiquing the Concept of BCI Illiteracy,” Sci. Eng. Ethics, vol. 25, no. 4, pp. 1217–1233, 2018, doi: 10.1007/s11948-018-0061-1.
7. P. Berndt, M. Hovestadt, and O. Kao, “Architecture for realizing cloud-based IT infrastructures,” Proc. - 2012 8th Int. Conf. Comput. Technol. Inf. Manag. ICCM 2012, vol. 2, pp. 794–799, 2012.
8. R. N. Calheiros, R. Ranjan, A. Beloglazov, C. A. F. De Rose, and R. Buyya, “CloudSim: a toolkit for modeling and simulation of cloud computing environments and evaluation of resource provisioning algorithms,” Softw. Pract. Exp., vol. 41, no. 1, pp. 23–50, Jan. 2011, doi: 10.1002/spe.995.
9. J. Kumar, A. Malik, S. K. Dhurandher, and P. Nicopolitidis, “Demand-Based Computation Offloading Framework for Mobile Devices,” IEEE Syst. J., vol. 12, no. 4, pp. 3693–3702, Dec. 2018, doi: 10.1109/JSYST.2017.2706178.
10. T. Lorido-Botran, J. Miguel-Alonso, and J. A. Lozano, “A Review of Auto-scaling Techniques for Elastic Applications in Cloud Environments,” J. Grid Comput., vol. 12, no. 4, pp. 559–592, 2014, doi: 10.1007/s10723-014-9314-7.

11. V. Aggarwal, M. Mathur, and N. Saraswat, "Comprehensive Cloud Incremental Data- Application Migration – A Proposed Model for Cloud Migration," no. July 2013, 2015.
12. S. Abolfazli, Z. Sanaei, E. Ahmed, A. Gani, and R. Buyya, "Cloud-based augmentation for mobile devices: Motivation, taxonomies, and open challenges," IEEE Commun. Surv. Tutorials, vol. 16, no. 1, pp. 337–368, 2014, doi: 10.1109/SURV.2013.070813.00285.
13. V. Khurana et al., "A Survey on Neuromarketing Using EEG Signals," IEEE Trans. Cogn. Dev. Syst., vol. 13, no. 4, pp. 732–749, 2021, doi: 10.1109/TCDS.2021.3065200.
14. Z. Wang, Y. Yu, M. Xu, Y. Liu, E. Yin, and Z. Zhou, "Towards a Hybrid BCI Gaming Paradigm Based on Motor Imagery and SSVEP," Int. J. Hum. Comput. Interact., vol. 35, no. 3, pp. 197–205, 2019, doi: 10.1080/10447318.2018.1445068.
15. S. Burwell, M. Sample, and E. Racine, "Ethical aspects of brain computer interfaces: A scoping review," BMC Med. Ethics, vol. 18, no. 1, pp. 1–11, 2017, doi: 10.1186/s12910-017-0220-y.
16. P. Sheoran and J. S. Saini, "Optimizing channel selection using multi-objective FODPSO for BCI applications," Brain-Computer Interfaces, vol. 9, no. 1, pp. 7–22, 2022, doi: 10.1080/2326263X.2021.1966985.
17. S. Kumar, H. Alawieh, and F. S. Racz, "Transfer learning promotes acquisition of individual BCI skills," PNAS Nexus, vol. 3, no. 2, pp. 1–15, 2024, doi: 10.1093/pnasnexus/pgae076.
18. M. Li and D. Xu, "Transfer Learning in Motor Imagery Brain Computer Interface: A Review," Journal of Shanghai Jiaotong University (Science). Aug. 19, 2022, doi: 10.1007/s12204-022-2488-4.
19. C. M. McCrimmon et al., "Performance Assessment of a Custom, Portable, and Low-Cost Brain-Computer Interface Platform," IEEE Trans. Biomed. Eng., vol. 64, no. 10, pp. 2313–2320, 2017, doi: 10.1109/TBME.2017.2667579.
20. Y. Kumar, J. Kumar, and P. Sheoran, "Integration of cloud computing in BCI: A review," Biomed. Signal Process. Control, vol. 87, no. PA, p. 105548, 2024, doi: 10.1016/j.bspc.2023.105548.
21. X. Wang and Z. Jin, "An Overview of Mobile Cloud Computing for Pervasive Healthcare," IEEE Access, vol. 7, pp. 66774–66791, 2019, doi: 10.1109/ACCESS.2019.2917701.
22. G. Muhammad, F. Alshehri, F. Karray, A. El Saddik, M. Alsulaiman, and T. H. Falk, "A comprehensive survey on multimodal medical signals fusion for smart healthcare systems," Inf. Fusion, vol. 76, no. July, pp. 355–375, 2021, doi: 10.1016/j.inffus.2021.06.007.
23. R. S. Chang, J. Gao, V. Gruhn, J. He, G. Roussos, and W. T. Tsai, "Mobile cloud computing research - Issues, challenges, and needs," Proc. - 2013 IEEE 7th Int. Symp. Serv. Syst. Eng. SOSE 2013, pp. 442–453, 2013, doi: 10.1109/SOSE.2013.96.
24. J. Kumar, A. Rani, and S. K. Dhurandher, "Convergence of user and service provider perspectives in mobile cloud computing environment: Taxonomy and challenges," Int. J. Commun. Syst., vol. 33, no. 18, pp. 1–38, 2020, doi: 10.1002/dac.4636.
25. A. Shakarami, A. Shahidinejad, and M. Ghobaei-Arani, "A review on the computation offloading approaches in mobile edge computing: A game-theoretic perspective," Softw. - Pract. Exp., vol. 50, no. 9, pp. 1719–1759, 2020, doi: 10.1002/spe.2839.
26. C. Shi, K. Habak, P. Pandurangan, M. Ammar, M. Naik, and E. Zegura, "COSMOS: Computation offloading as a service for mobile devices," Proc. Int. Symp. Mob. Ad Hoc Netw. Comput., vol. 11-14-Augu, pp. 287–296, 2014, doi: 10.1145/2632951.2632958.
27. N. Chauhan, R. Agrawal, and K. Garg, "Opportunities and challenges for smart healthcare system in fog computing," Comput. Intell. Healthc. Appl., pp. 13–31, Jan. 2022, doi: 10.1016/B978-0-323-99031-8.00014-4.
28. R. Moreno-Vozmediano, R. S. Montero, E. Huedo, and I. M. Llorente, "Efficient resource provisioning for elastic Cloud services based on machine learning techniques," J. Cloud Comput., vol. 8, no. 1, 2019, doi: 10.1186/s13677-019-0128-9.
29. S. Vankadara and N. Dasari, "Energy-aware dynamic task offloading and collective task execution in mobile cloud computing," International Journal of Communication Systems, vol. 33, no. 13. 2020, doi: 10.1002/dac.3914.
30. J. K. Zao et al., "Pervasive brain monitoring and data sharing based on multi-tier distributed computing and linked data technology," Front. Hum. Neurosci., vol. 8, no. JUNE, 2014, doi: 10.3389/fnhum.2014.00370.
31. A. Jafarifarmand and M. A. Badamchizadeh, "Real-time multiclass motor imagery brain-computer interface by modified common spatial patterns and adaptive neuro-fuzzy classifier," Biomed. Signal Process. Control, vol. 57, p. 101749, 2020, doi: 10.1016/j.bspc.2019.101749.
32. Physionet, "Physionet - EEGMMIDB dataset." https://physionet.org/content/eegmmidb/1.0.0/%0A.
33. C. Aarset, "A global optimum-informed greedy algorithm for A-optimal experimental design," pp. 1–7, 2024, [Online]. Available: http://arxiv.org/abs/2409.09963.
34. Y. Kumar, J. Kumar, and P. Sheoran, "Auto-Scaling Framework for Enhancing the Quality of Service in the Mobile Cloud Environments," Comput. Mater. Contin., vol. 75, no. 3, pp. 5785–5800, 2023, doi: 10.32604/cmc.2023.039276.

Interpretable Machine Learning in Healthcare: An XAI Approach for Diabetes Prediction

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ABSTRACT

By enabling advancements in diagnostics, treatment planning, and patient management, Artificial Intelligence (AI) has emerged as a transformative force in healthcare. However, in sensitive domains like healthcare, the "black box" nature of many machine learning models impedes trust and adoption. Explainable AI (XAI) addresses this challenge by providing transparency and interpretability to AI-driven decisions. Using a variety of XAI approaches, including SHAP, LIME, PDP, ALE, and CEM, this study examines the predictions of XGBoost and CatBoost models trained on the Pima Indian Diabetes Dataset. The observed results highlight the importance of variables such as age, BMI, and glucose in the prediction of diabetes and are consistent with clinical knowledge. The integration of these explainability methods allows the research to demonstrate how XAI can enhance trust, improve decision-making, and ensure ethical use of AI in the field of healthcare.

KEYWORDS *: XAI, XGBoost, CatBoost, SHAP, LIME, PDP, CEM, ALE, Healthcare, PIMA.*

INTRODUCTION

With its immense impact in various sectors, Artificial Intelligence supports diagnostics, disease prediction, and personalized treatment planning in the healthcare sector. Due to the "black box" nature of many models, the widespread adoption of AI in clinical settings is limited despite these advancements. These black-box decision-making processes being opaque makes it difficult for stakeholders, i.e., patients and clinicians, to trust AI-driven recommendations, especially in high-stakes situations. By giving AI models interpretability and transparency, Explainable AI (XAI) aims to alleviate these worries to a major extent. Methods such as feature attribution, visualization, and instance-level explanations are employed by XAI to help stakeholders comprehend the reasoning behind AI predictions. This understanding improves the ethical use of AI in healthcare applications by building trust and reducing biases. This study analyzes the performance and interpretability of machine learning models trained in the Pima Indian Diabetes Dataset by employing XAI techniques and aims to bridge the gap between clinical trust and AI capabilities.

LITERATURE ANALYSIS

Explainable AI Techniques

A range of XAI methods has been developed to address the interpretability challenges of machine learning models. SHAP (SHapley Additive Ex Planations) [2], [18], [19] is one of the most widely used techniques, rooted in cooperative game theory. It provides both local and global explanations. Similarly, LIME (Local Interpretable Model-agnostic Explanations) [3], [20] approximates the model's behavior locally, offering insights into individual predictions. LIME necessitates careful validation. Partial Dependence Plots (PDP) [4], [21] and Accumulated Local Effects (ALE) [5], [22] are global interpretability techniques that visualize the relationships between features and model predictions. PDP calculates the average marginal effect of a feature, while ALE accounts for feature dependencies, making it more robust. ELI5 [7], [23] simplifies the explanation process, offering intuitive insights into feature contributions in tree-based models like XGBoost [8], [24] and CatBoost [9], [25]. Table I represents comparison among explainability techniques including SHAP, LIME, EL5, PDP, and ALE on grounds of their type of explainability along with a description of the technique and its use case.

Table 1: Comparison of Explainability Models

Technique	Type	Description	Use Case
SHAP	Local & Global	Distributes feature importance based on cooperative game theory.	Uncovers individual predictions and global feature interactions.
LIME	Local	Perturbs data around an instance to understand feature influence.	Explains specific predictions to assist clinicians.
ELI5	Local & Global	Provides concise explanations for linear and tree-based models.	Useful for initial exploration of feature importance.
PDP	Global	Visualizes the marginal effect of individual features on predictions.	Highlights overall model behavior and critical features.
ALE	Global	Improves upon PDP by reducing bias caused by feature correlations.	Provides more accurate insights into global feature importance.

Interpretability

Interpretability is indispensable in XAI research today. The research community has recognized this interpretability problem and focused on developing both interpretable models and explanation methods over the past few years. The articles [12] and [13] and papers [14], [15], [17] and [26] provide a review of the current state of the research in the field and present objective metrics for how explainable artificial intelligence (XAI) can be quantified.

Applications of XAI in Healthcare

Several studies highlight the importance of XAI in healthcare decision-making. For instance, XAI has been pivotal in diagnosing diseases, predicting patient outcomes, and identifying risk factors. A study explored the role of SHAP and LIME in making AI models transparent, emphasizing their application in domains like healthcare and finance [10]. Another review [11] examined the use of XAI in mitigating biases and ensuring fairness in AI-driven healthcare systems. The papers [27] and [28] explores the application of XAI in medicine & diagnosis and surgery. Despite the challenges, the literature underscores the transformative potential of XAI in building trustworthy, ethical, and reliable AI systems for critical applications like healthcare.

Challenges and Limitations

Despite its promise, XAI faces several challenges. The computational complexity of some techniques, especially for large datasets or deep learning models, can limit their scalability. Additionally, many studies focus on theoretical aspects of XAI without providing practical implementation details, hindering their applicability in real-world scenarios. Ensuring consistency across different XAI methods and aligning interpretability with domain-specific requirements remain ongoing challenges.

DATASET OVERVIEW

The foundation for this study is The Pima Indian Diabetes Dataset [1]. It consists of medical records of women of the Pima Indian heritage, including crucial features such as glucose levels, BMI, age, and blood pressure. Whether a patient has diabetes is indicated by the dataset's target variable. The dataset includes eight important features, each with clinical relevance:

- Glucose: It is a critical marker of diabetes risk. Its high variability indicates its significance in diabetes predictions.
- BMI: Body Mass Index is a measure of obesity, and it is strongly correlated with diabetes.
- Age: This factor reflects the patient demographic, with older individuals at higher risk.
- Blood Pressure: Here diastolic blood pressure is represented, and it is relevant to cardiovascular health.
- Diabetes Pedigree Function: It indicates the hereditary risk of diabetes based on family history.
- Pregnancies: The number of times a patient has been pregnant can directly affect diabetes susceptibility.
- Skin Thickness: It measures subcutaneous fat which is used as an indirect measure of body fat.
- Insulin: 2-hour serum insulin levels are represented which are linked to glucose metabolism.

The clinical relevance and diversity of this dataset make it an ideal candidate for evaluation of the interpretability of machine learning models in healthcare. The summary of all the features that affect the prediction along with their range of values and mean are represented in the Table 2.

Table 2: Summary of Features and Statistics

Feature	Mean	Range (Min-Max)
Glucose	120.89	0–199
BMI	31.99	0–67.1
Age	33.24	21–81
Blood Pressure	69.11	0–122
Diabetes Pedigree Function	0.47	0.078–2.42
Pregnancies	3.85	0–17
Skin Thickness	20.53	0–99
Insulin	79.79	0–846

METHODOLOGY

A combination of machine learning models and XAI techniques are employed in this study to perform analysis on the Pima Indian Diabetes Dataset. The workflow includes data preprocessing, model training, and the application of interpretability methods along with visualizations to understand how features influence the decision-making process.

Model Training

XGBoost and CatBoost were chosen for their high performance on tabular data. Both models employ gradient boosting to optimize predictions, with CatBoost offering native support for categorical features, which contributes to its superior accuracy compared to XGBoost.

Explainability Techniques

The following XAI techniques were used to interpret model predictions:

- SHAP (SHapely Additive exPlanations): Provides both global and local feature importance by distributing contributions among features based on cooperative game theory, ensuring consistency and fairness in explanations.
- LIME (Local Interpretable Model-agnostic Explanations): Focuses on explaining individual predictions by approximating the model's behavior using a simpler, interpretable surrogate model trained on perturbed samples.
- ELI5(Explain Like I'm 5): Enhances interpretability by visualizing feature importance rankings, offering intuitive explanations for complex models, particularly tree-based algorithms like random forests and gradient boosting.
- PDP (Partial Dependence Plot): Illustrates the marginal effect of a feature on model predictions by averaging predictions over the dataset while varying the feature of interest, assuming independence from other features.
- ALE (Accumulated Local Effects): Addresses the limitations of PDP by considering the correlations of features, providing a more reliable estimate of the impact of a feature without assuming independence.

Visualization Techniques

To enhance interpretability, multiple visualization techniques were applied to understand how model predictions are influenced by different features.

i. Feature Distribution Visualization: A gradient-colored statistical summary of the data set was generated to visualize the distribution of each characteristic, providing information on the range and variance.

ii. SHAP-Based Visualizations:

- Summary Plot: Displays global feature importance by ranking features based on their average impact on model output.
- Bar Plot: Concise visualization of the importance of the features.
- Dependence Plot: Reveals how a particular feature affects the model output while considering interactions with other features.
- Force Plot (Local Explanation for a Single Instance): Highlights how each feature contributes to an individual prediction (red increases, blue decreases).
- Force Plot (Multiple Instances): Displays contributions for multiple predictions in a compact format, identifying trends across the dataset.

iii. LIME-Based Visualizations:

- Tabular Explanation: Provides feature contributions for individual predictions using a surrogate model.
- Bar Plot Representation: Shows the weight of each feature in the decision-making process.

iv. ELI5 Feature Importance Plot: Uses permutation importance to measure how the model's performance changes when feature values are randomly shuffled. Error bars indicate variability, highlighting feature stability.

v. Partial Dependence Plots (PDP): Displays how a specific feature influences the model's output by varying its value while keeping other features

constant. Visualizations were generated for key features such as glucose levels, blood pressure, and BMI.

vi. Accumulated Local Effects (ALE): ALE addresses the limitations of PDP by considering feature correlations, providing a more reliable estimation of a feature's impact without assuming independence.

Interpretability Techniques

For high-stakes applications of machine learning like healthcare, we need to ensure that models not only make accurate predictions but also provide interpretable explanations. The following quantifiable metrics help measure interpretability and can be used to evaluate models like XGBoost and CatBoost using XAI methods such as SHAP, LIME, PDP, ALE, ELI5, and SME.

i. Fidelity (Faithfulness): Fidelity measures how accurately an explanation reflects the actual decision-making process of the model. It compares the model's output with and without the key features highlighted in the explanation. If the model behaves the same way, fidelity is high. High fidelity ensures that the explanations are trustworthy. Example: If SHAP explains that "Age" is the most critical factor for a prediction, but removing it doesn't change the model's decision, then fidelity is low.

ii. Stability: It measures how much the explanation changes when we slightly modify the input. It runs the model with small perturbations of the input and checks if the explanation remains similar. Stable explanations ensure robustness and reliability. Example: Two patients with nearly identical symptoms should get similar explanations. If a minor change in patient data leads to a completely different explanation, it indicates instability.

iii. Sparsity: It checks if the explanation is concise, using only the most essential features. It counts the number of nonzero coefficients in an explanation. fewer, more relevant features lead to better interpretability. Example: An explanation that uses 3 key factors instead of 10 is easier to interpret.

iv. Monotonicity: It ensures that increasing a feature's value has a consistent effect on the prediction. It checks whether an increase in a feature always leads to an increase (or decrease) in the model's output. Logical and predictable relationships between features and predictions is an ideal outcome. Example: If increasing "Age" sometimes increases disease risk but sometimes decreases it, the model lacks monotonicity.

v. Locality Preservation: It ensures that similar inputs produce similar explanations. It computes explanation similarity between pairs of similar inputs. Similar cases should get similar explanations. Example: Two patients with nearly identical lab results should receive the same reasoning for a diagnosis.

vi. Feature Importance Stability: It measures how consistent feature importance rankings are in multiple runs. It compares rankings of feature importance across different training sessions. Feature importance should be stable across runs. Example: if "Blood Pressure" is the most important factor today but irrelevant tomorrow, the model is unstable.

vii. Compactness: It measures how simple the explanation is. It evaluates the length or depth of the explanation. The simpler the explanation the better. Example: A decision tree with 3 rules is easier to understand than one with 30 rules.

RESULTS AND DISCUSSION

SHAP

i. Global Explanations

SHAP analysis provides a comprehensive understanding of how individual features influence model predictions both globally and locally. The summary plots, including bar charts and scatter plots, highlight Glucose, BMI, and Age as the most significant factors in predicting diabetes. Among these, Glucose has the highest global importance, indicating a strong correlation with diabetes outcomes. BMI and Age also play a crucial role, though their influence is slightly lower.

Figure 1 presents a scatter plot of SHAP values, which reveals a clear directional trend: higher Glucose and BMI values positively contribute to predicting diabetes, whereas lower values have a negative effect. This pattern aligns with medical insights, reinforcing the model's reliability in identifying risk factors.

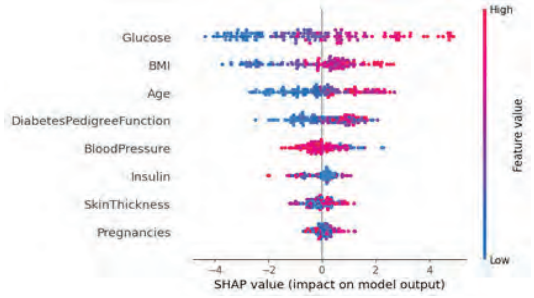

Fig. 1: Scatter plot of SHAP values

The monotonicity of SHAP was 0.375 for both models, demonstrating stable and consistent feature contributions across different samples. The sparsity factor of 1.0 suggests that both models exhibited highly consistent SHAP values across different samples, reinforcing their reliability in interpretability. The SHAP stability score of 1.1750 further indicates that feature attributions remained stable despite potential variations in the dataset.

ii. Local Explanations

SHAP force plots for individual predictions revealed that both CatBoost and XGBoost made similar feature attributions, with key features such as Glucose, BMI, and Age playing dominant roles. A dependence plot for Glucose is illustrated in the Figure 2 where it demonstrates how with varying BMI levels the SHAP value changes. A synergistic effect is suggested by the increasing trend - the impact of Glucose is amplified by higher BMI on the diabetes predictions.

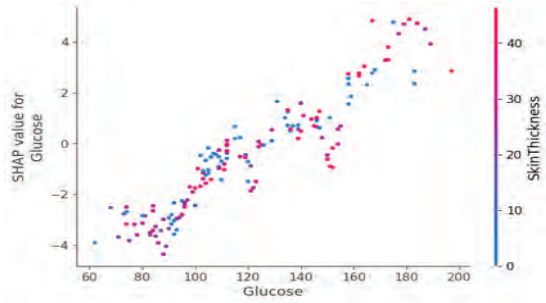

Fig. 2: Dependence plot for SHAP value for Glucose

A force plot for a specific sample is presented in Figure 3; it breaks down how individual features contribute to the final prediction. The features that favor a diabetes diagnosis are represented in red, whereas the ones in blue are features that reduce the likelihood of diagnosis. The visual representation provides an intuitive breakdown of model decisions, making the interpretation of local-level predictions easier.

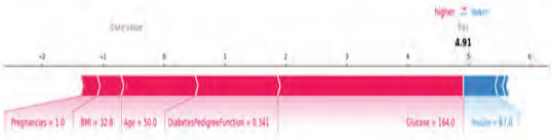

Fig. 3: Force Plot of Sample Outcome

LIME

Local Interpretable Model-agnostic Explanations (LIME) provides instance-specific interpretations by explaining why a model made a particular prediction for a given data point. It identifies the most influential features for individual predictions, offering insights into the model's decision-making process. To illustrate, LIME highlights cardinal variables like Glucose and BMI when analyzing instances such as 50 and 100. This aligns with the findings of other interpretability methods. The LIME visualizations assign ranks to features based on their contribution, indicating the positive or negative impact they have on the prediction. This fine-grained approach not only validates the model's predictions but also reinforces trust in its behavior by complementing other interpretability techniques.

The LIME explanation for Instance 100 is illustrated in Figure 4, where the visualization depicts the contribution of different feature towards the final prediction. It highlights how individual feature values impact the predicted outcome. Meanwhile, Figure 5 represents the feature importance for the same instance, showcasing the relative weight of each feature in influencing the model's decision. The computed metrics for Instance 100 show that both CatBoost and XGBoost achieve an accuracy of 98.12%, with a minimal standard deviation of 0.0206. The minimum and maximum values range from 0.6343 to 0.9634 for CatBoost and 0.6055 to 0.9634 for XGBoost, demonstrating the stability of feature attributions. The feature importance ranking provided by LIME further strengthens interpretability by revealing the magnitude and direction of each feature's influence on the prediction.

These visualizations collectively provide a deeper understanding of model interpretability, ensuring transparency in predictive analysis. LIME's ability to generate instance-specific explanations enhances the credibility of the model, making it more accessible and interpretable for stakeholders.

Fig. 4: LIME Feature Importance for Instance 100

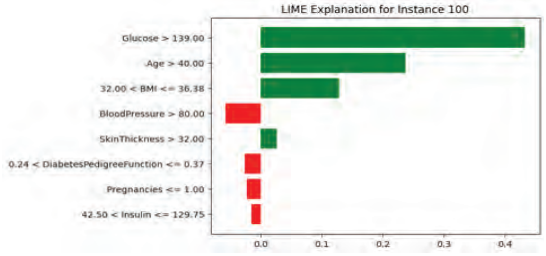

Fig. 5: LIME Prediction for Instance 100

ELI5

ELI5 provides a quantitative assessment of feature importance by systematically permuting feature values and measuring the corresponding change in the model's predictive accuracy.

The metric evaluation for ELI5 applied to CatBoost and XGBoost. The Compactness metric for both models stands at 98.00, indicating high interpretability. However, the Feature Stability is 0.0, suggesting that the explanations remain highly sensitive to perturbations. The Fidelity scores of 0.5886 (CatBoost) and 0.5739 (XGBoost) highlight moderate agreement between ELI5-generated explanations and actual model predictions. Moreover, Locality Preservation is recorded as 0.0, meaning that local explanations may not be entirely representative of global model behavior. Monotonicity and Sparsity values remain at 1.0, reinforcing consistency and simplicity in explanation generation. Notably, Stability is significantly lower (0.0361 for CatBoost and 0.0361 for XGBoost), indicating variability in feature importance rankings across different iterations.

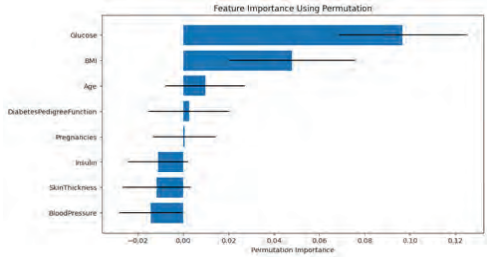

Fig. 6: ELI5 Feature Importance Bar Chart

Figure 6 presents the ELI5 feature importance chart, depicting the relative weight of each feature in influencing the model's predictions. The chart highlights Glucose, BMI, and Age as the most critical predictors of diabetes, aligning with the findings from SHAP and LIME. The presence of error bars in the figure indicates the variability in importance scores across multiple iterations, reinforcing the robustness of the analysis.

PDP

PDPs visually illustrate the impact of individual features on model predictions while keeping all other features constant. This approach helps in understanding the marginal effect of each feature on the predicted outcome, offering insights into how specific variables influence the model's decision-making process. The Compactness metric for PDP is 0.3436 for both CatBoost and XGBoost, suggesting that while PDPs offer valuable interpretability, they may not be as succint as other methods. The Feature Stability is relatively low (0.0051), indicating that small changes in feature values can lead to variations in the partial dependence estimates. Fidelity scores of 0.5844 (CatBoost) and 0.5765 (XGBoost) indicate moderate agreement between PDP insights and actual model behavior. Moreover, Locality Preservation is high (0.9287), confirming that PDPs maintain consistency in feature effects across nearby values. Monotonicity is 0.4902, reflecting the mixed nature of feature impact trends, while Sparsity remains at 0.0, implying that PDPs do not inherently focus on a limited subset of features for explanation. Lastly, the Stability metric (0.0713 for both models) suggests moderate variation in PDP outputs across multiple runs.

The PDP for Glucose reveals a strong, nearly linear positive relationship with diabetes risk, indicating that higher glucose levels consistently increase the probability of a positive diagnosis. BMI follows a similar trend, with diabetes risk rising as BMI increases; however, the effect plateaus at higher BMI values, suggesting diminishing returns in its influence. Age has a moderate but steady impact, with predictions gradually increasing as age advances, reinforcing established medical insights.

Figure 7 presents the Partial Dependence Plot (PDP) for Glucose, illustrating how the number of pregnancies influences diabetes risk.

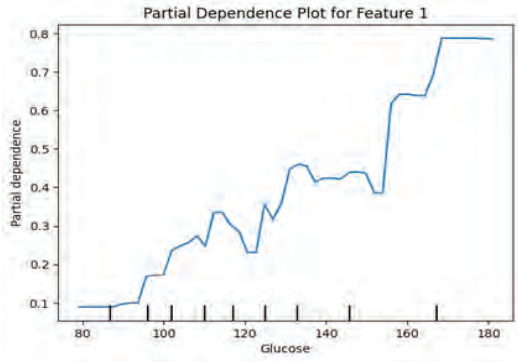

Fig. 7: PDP for Glucose

ALE

Accumulated Local Effects (ALE) plots provide an alternative to Partial Dependence Plots (PDPs), offering an alternative to representation of how individual features influence model predictions while adjusting for the local distribution of feature values. Unlike PDPs, which assume feature independence, ALE accounts for

correlations, making it a more reliable tool for interpreting feature importance in complex models. As shown in The compactness of ALE is 0.4123 for both CatBoost and XGBoost, indicating that ALE maintains a slightly more concise representation compared to PDPs. The Feature Stability metric is 0.0048, suggesting that minor variations in feature values have minimal impact on ALE estimates. Fidelity scores of 0.5621 (CatBoost) and 0.5548 (XGBoost) reflect moderate alignment between ALE and the model's actual predictions, while Locality Preservation remains high at 0.8854, indicating that ALE effectively captures localized feature effects. Monotonicity is 0.4716, signifying a generally consistent but slightly variable trend in feature influence, while Sparsity is 0.0, meaning ALE does not inherently focus on a subset of features. Lastly, the Stability metric of 0.0685 across both models suggests relatively consistent outputs across different iterations.

In this analysis, Glucose and BMI once again emerge as dominant factors, with strong Accumulated Local Effects (ALE) values reinforcing their significant impact on diabetes risk. The ALE plot for Glucose (Figure 8) shows a consistent positive effect across its range, indicating that as glucose levels increase, the likelihood of diabetes also rises. Meanwhile, BMI and Age exhibit relatively smaller but still noticeable effects, aligning with their roles as secondary yet influential predictors. The differences between the ALE and PDP results highlight nuanced interactions within the data, suggesting that feature dependencies may influence the model's predictions. These insights could guide further investigation into how feature interactions shape the model's decision-making process. These visualizations offer a comprehensive view of how feature importance varies locally, further enhancing the model's interpretability.

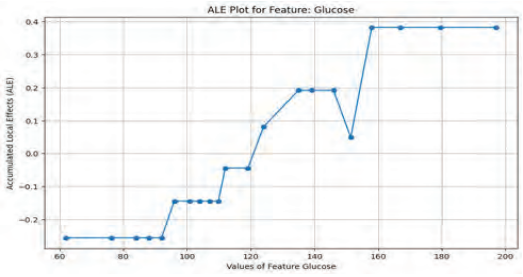

Fig. 8: ALE for Glucose

CONCLUSION

This study highlights the critical role of Explainable AI (XAI) in making machine learning models for the prediction of diabetes more transparent, interpretable, and trustworthy. Using multiple interpretability techniques, including SHAP, LIME, ELI5, PDP, ALE, and CEM, we gain a comprehensive understanding of the contributions of the features and the behavior of the model. Across all the methods, Glucose, BMI, and Age consistently emerge as the strongest predictors, reinforcing their well-established importance in the assessment of diabetes risk. Global methods, such as SHAP summary plots and ELI5, provide an overarching view of feature influence, while local techniques, like LIME and SHAP force plots, explain individual predictions. CEM adds a unique perspective by identifying the minimal feature changes needed to alter a prediction, offering actionable insights that can guide personalized patient interventions. For example, it can determine how small adjustments in glucose or BMI levels could shift a classification from Diabetes to No Diabetes, making it particularly useful in clinical decision making. Further underscored is the significance of model selection in predictive healthcare applications by the comparison between XGBoost and CatBoost. CatBoost's superior accuracy (75.3%) depicts superior handling of complex feature interactions, even though strong predictive capabilities are demonstrated by both the models. The need for models that align with medical knowledge and interpretability standards, along with delivering high accuracy, is reinforced by this. This analysis ultimately shows how XAAI bridges the gap between complex model predictions and real-world decision-making, empowering both clinicians and data scientists alike to make informed, transparent and actionable decisions. Integration of these insights into healthcare can enable us to move towards more reliable and efficient AI-driven solutions for the management and prediction of diseases.

FUTURE SCOPE

The future of diabetes diagnosis and management lies in the seamless integration of predictive models into real-time Clinical Decision Support Systems (CDSS), enabling healthcare providers to receive personalized risk assessments, early warnings, and tailored treatment recommendations directly linked to patient records. This would promote timely, data-driven decisions and improve the overall quality of care. To ensure robustness and fairness, it is essential that these models are validated across diverse populations encompassing various regions, ethnicities, age groups, and socio-economic backgrounds, enhancing their generalizability and global applicability. Future work should also explore the incorporation of longitudinal and multi-modal data, including continuous

glucose monitoring, wearable devices, genetic information, and lifestyle data. Such integration would support time-series analysis, allowing the models to track disease progression, predict complications, and shift diabetes care towards preventive, proactive management. Additionally, as Explainable AI (XAI) techniques advance, optimizing models using interpretability insights-such as those from contrastive explanations and human-in-the-loop systems-will enhance transparency and clinical trust. Finally, real-world deployment requires collaboration with healthcare institutions and regulatory authorities to ensure compliance with medical AI standards, address ethical concerns, and safeguard data privacy, ultimately supporting safe and effective clinical adoption.

REFERENCES

1. The Pima Indian Diabetes Dataset. URL: https://www.kaggle.com/datasets/uciml/pima-indians-diabetes-database
2. https://github.com/shap/shap
3. https://github.com/marcotcr/lime
4. https://www.kaggle.com/code/dansbecker/partial-dependence-plots
5. https://github.com/blent-ai/ALEPython
6. Labaien, J., Zugasti, E., De Carlos, X. (2020). Contrastive Explanations for a Deep Learning Model on Time-Series Data. In: Song, M., Song, IY., Kotsis, G., Tjoa, A.M., Khalil, I. (eds) Big Data Analytics and Knowledge Discovery. DaWaK 2020. Lecture Notes in Computer Science(), vol 12393. Springer, Cham.
7. Kawakura, S., Hirafuji, M., Ninomiya, S., & Shibasaki, R. (2022). Adaptations of Explainable Artificial Intelligence (XAI) to Agricultural Data Models with ELI5, PDPbox, and Skater using Diverse Agricultural Worker Data. European Journal of Artificial Intelligence and Machine Learning, 1(3), 27–34.
8. Tianqi Chen and Carlos Guestrin. 2016. XGBoost: A Scalable Tree Boosting System. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '16). Association for Computing Machinery, New York, NY, USA, 785–794.
9. Hancock, J.T., Khoshgoftaar, T.M. CatBoost for big data: an interdisciplinary review. J Big Data 7, 94 (2020).
10. https://github.com/interpretml/interpret
11. https://www.researchgate.net/publication/367462968_Explainable_AI_XAI_and_its_Applications_in_Building_Trust_and_Understanding_in_AI_Decision_Making
12. https://www.mdpi.com/2079-9292/8/8/832
13. https://onlinelibrary.wiley.com/doi/abs/10.1111/coin.12410
14. https://arxiv.org/abs/2106.08492
15. https://arxiv.org/abs/1901.08558
16. Chaddad, A.; Peng, J.; Xu, J.; Bouridane, A. Survey of Explainable AI Techniques in Healthcare. Sensors 2023, 23, 634. https://doi.org/10.3390/s23020634
17. https://doi.org/10.1613/jair.1.13283
18. Edoardo Mosca, Ferenc Szigeti, Stella Tragianni, Daniel Gallagher, and Georg Groh. 2022. SHAP-Based Explanation Methods: A Review for NLP Interpretability. In Proceedings of the 29th International Conference on Computational Linguistics, pages 4593–4603, Gyeongju, Republic of Korea. International Committee on Computational Linguistics.
19. Garreau, D. &; Luxburg, U.. (2020). Explaining the Explainer: A First Theoretical Analysis of LIME. Proceedings of the Twenty Third International Conference on Artificial Intelligence and Statistics, in Proceedings of Machine Learning Research 108:1287-1296
20. Churchland, P.M. (1995). On the Nature of Explanation: A PDP Approach. In: Misiek, J. (eds) The Problem of Rationality in Science and its Philosophy. Boston Studies in the Philosophy of Science, vol 160. Springer, Dordrecht. https://www.google.com/search?q=https://doi.org/10.1007/978-94-011-0461-6_6
21. https://doi.org/10.1016/B978-0-323-95879-0.50251-4
22. Saha, S., 2018. A comprehensive guide to convolutional neural networks—the ELI5 way. Towards data science, 15, p.15.
23. Nielsen, D., 2016. Tree boosting with xgboost-why does xgboost win" every" machine learning competition? (Master's thesis, NTNU).
24. Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A.V. and Gulin, A., 2018. CatBoost: unbiased boosting with categorical features. Advances in neural information processing systems, 31.
25. Linardatos, P., Papastefanopoulos, V. and Kotsiantis, S., 2020. Explainable ai: A review of machine learning interpretability methods. Entropy, 23(1), p.18.
26. Tjoa, E. and Guan, C., 2020. A survey on explainable artificial intelligence (xai): Toward medical xai. IEEE transactions on neural networks and learning systems, 32(11), pp.4793-4813.
27. [27] Zhang, Y., Weng, Y. and Lund, J., 2022. Applications of explainable artificial intelligence in diagnosis and surgery. Diagnostics, 12(2), p

Empirically Analysing Deep learning towards Enhanced Stock Market Prediction: A Model Comparison

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ABSTRACT

Predicting the stock market is a difficult problem, largely due to the volatility and non-periodic nature of financial data. Models based on deep learning — Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Transformers and variational autoencoders (VAE) — have proven their potential to capture temporal dependencies in data composed of aligned time-series relevant to finance. In this study, the performance of these models on stock price data of five pharmaceutical companies has been compared, namely Cipla, Glenmark Pharmaceuticals, Pfizer, Sun Pharmaceuticals and Merck, on the basis of Mean Squared Error (MSE), Mean Absolute Error (MAE) and R^2 score. The results show that GRU has the lowest mean square error (MSE) (0.012), mean absolute error (MAE) (0.024) and (R^2) (0.93) among all models, which suggests that it is the most effective model for predicting stock prices shortly. On the other hand, Transformer models had a higher error rate (MSE: 0.056, R^2: 0.67), indicating a poor performance in capturing short-term price movements. The results underscore the efficiency offered by GRU for financial forecasting, and future work will involve investigating the application of hybrid GRU-Transformer models to further improve predictive accuracy.

***KEYWORDS** : Stock market prediction, Deep learning, GRU, LSTM, Transformer, Time-series forecasting, Real-world Financial data.*

INTRODUCTION

The increasing attention given to researchers on stock market prediction is based on the advances in machine learning (ML) techniques, primarily because traditional statistical models fail to handle the complexities of financial data. Classical approaches such as Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) have been widely applied for financial forecasting. However, such methodologies suffer from a weakness in capturing the highly volatile and nonlinear dependencies contained within the movements of stock prices [1][2]. So, the practice now is slowly drifting towards ML-based approaches that are better suited for modeling the complex relationships found in time-series data [3].

One of the first deep learning models used in the related applications was the Recurrent Neural Network (RNN). Although RNNs introduced improvements over statistical models, they were notorious for suffering from the vanishing gradient problem, which prevents learning long-term dependencies over financial time series [4]. Advances in neural networks addressed all these challenges and greatly improved prediction accuracy. LSTM networks were established to overcome these weaknesses by utilizing different mechanisms in which gating has been used to retain important information over long periods of time [5] [6]. Gated Recurrent Units (GRUs) have also emerged as a computationally more efficient alternative to LSTMs with comparable performance but fewer parameters and faster training times [7][8].

Recent years have witnessed Transformer models coming into prominence in financial time-series forecasting. Unlike the RNNs that process sequences serially, the Transformers use self-attention mechanisms that facilitate parallelized computations and enhance both efficiency

and predictive performance [9]. Variants such as BERT do better in terms of stock market prediction accuracy as compared with RNN, LSTM, and GRU-based models and present a better trade-off between precision and execution time [10, 11]. These developments reflect the growing role of deep learning in financial markets, where larger datasets and more sophisticated algorithms continue to drive improvements in predictive accuracy [12].

LITERATURE ANALYSIS

Stock market prediction has gained much focus from researchers with technological advances in machine learning (ML), especially since standard statistical models are ineffective to capture the complexity of the financial data. Conventionally, models like ARIMA and GARCH have been considered the workhorses for financial predictions. However, these techniques cannot capture highly volatile and nonlinear dependencies of the price movements of stocks1. There is an increasing trend to adopt ML-based methods that allow better capture of complex dynamics incorporated into time-series data [3].

The Recurrent Neural Network (RNN) was one of the very early deep learning models used to forecast the stock market. Although the RNNs provided similar variations from the proper statistical models, they were affected by the vanishing gradient problem, causing the long-term dependencies to be prominent in financial time-series data [4]. Neural networks overcome these challenges significantly increasing the accuracy of predictions. To address these drawbacks, Long Short-Term Memory (LSTM) networks were introduced as those establish specific gate mechanisms to preserve information over a large time interval [5]. Similarly, GRUs provided a more computationally efficient way than LSTMs with equivalent performance on fewer parameters and shorter training times [6].

Transformer models have emerged in the literature, in the last years, for financial time-series forecasting. In contrast with RNNs, which analyze sequences one by one, Transformers use self-attention mechanisms that enable parallelized computations, thus improving efficiency and predictive capacity [9]. Bidirectional Encoder Representations from Transformers (BERT) and its variants achieved an accuracy higher than the widely-used RNN-, LSTM-, and GRU-based models for stock market predictions, promising a better trade-off between accuracy and execution time [10]. news articles [12], and therefore these innovations suggest how deep learning is becoming more commonplace in financial markets as increasing datasets, and evolving algorithms, lead to growing predictive accuracy.

METHODOLOGY

The approach in this work is developed within a clear pipeline that includes data acquisition, preprocessing, model selection, training and eventual evaluation. The dataset contains the historical stock prices of Cipla, Sun Pharmaceuticals, Pfizer, Merck and Glenmark Pharmaceuticals, companies that are frequently examined in financial forecasting studies because of their relevance to the market. Data Preprocessing consists of MinMax scaling for normalization, outlier detection and missing value imputation by a linear interpolation method, which are known to increase the stability and accuracy of deep learning forecasting models for time-series data [13]. We split our data to train and test, so that we have a robust evaluation and do not overfit. The Loss function of RNN is depicted in equation (1), $y_t^{(c)}$ is the ground truth one-hot vector for class c at time step t and $\hat{y}_t^{(c)}$ is the predicted probability for class ccc at time step t, C is the number of output classes.

$$L = -\sum_{t=1}^{T} \sum_{c=1}^{C} y_t^{(c)} \log \hat{y}_t^{(c)} \quad (1)$$

The study proposes and compares four deep learning-based regression models Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU) and Transformers. RNNs are capable of modeling sequential dependencies but cannot retain long-term memory due to the problems of vanishing gradients. This limitation is relaxed by LSTM and GRU through the introduction of gating mechanisms that better preserve historical trends while GRUs provide a computationally efficient alternative [14]. They were a breakthrough: by using self-attention, Transformer-based models dispense with recurrence, are adept at capturing long-range dependencies, and allow for parallelization, thus, their suitability for huge stock market datasets. These models are trained with MSE as loss function and Adam optimizer with the most common used method in financial forecasting which tends to improve both convergence rates and prediction accuracy. The Loss function for LSTM is expressed in equation (2) and regression tasks, Mean Squared Error (3) is often used, Where y_t is the actual output at time t and $\hat{y}_t$ is the predicted output.

$$L = -\sum_{t=1}^{T} \sum_{c=1}^{C} y_t^{(c)} \log \hat{y}_t^{(c)} \quad (2)$$

$$L=\frac{1}{T}\sum_{t=1}^{T} (y_t - \hat{y}_t)^2 \quad (3)$$

For assessing model performance, the study utilizes Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-Squared ($\mathbb{R}^2$) Score; a holistic evaluation of predictive ability. The use of LSTMs and GRUs have shown good performance on sequential forecasting, while transformers showed generalization performance under volatile conditions [15]. The pharmaceutical industry is volatile in nature; therefore, the comparative efficiency of these models would be useful to select the suitable forecasting techniques for investment decisions in the stock market. Loss functions for GRU is expressed in equation (4) and regression of GRU is expressed in equation(5)

$$L= -\sum_{t=1}^{T} \sum_{c=1}^{C} y_t^{(c)} \log \hat{y}_t^{(c)} \quad (4)$$

$$L=\frac{1}{T}\sum_{t=1}^{T} (y_t - \hat{y}_t)^2 \quad (5)$$

Thus, the following steps proposed in this paper will allow for a more structured and replicable methodology for predicting stock market movement using deep learning. Maximising the efficiency and accuracy of the model suggests a potential area for future research to conduct hybrid models, merging LSTMs with attention mechanisms or including additional financial predictors, such as macroeconomic trends and investor sentiment analysis. Mean Squared Error Loss for Transformer is depicted in equation (6)

$$L_{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (6)$$

Dataset Description

This study looks at how selected pharmaceutical companies' stocks have performed by looking at their past stock prices and trading amounts. It includes market data from companies like Merck, Cipla, Glenmark Pharmaceuticals, Pfizer, and Sun Pharmaceuticals over several years to spot key patterns and changes in stock movements.

Table 1. shows important stats like the total number of days stocks were traded, the average closing price, and how much the price typically varies for each company. The 'count' tells us how many trading days were included, while the 'mean' shows the usual closing price during the time, giving us a view of the company's market value over time. The 'std' (standard deviation) shows how wildly stock prices changed from their average, pointing out the riskiness and unstable nature of the stock prices.

From Table 1. We see that some companies show steadier price trends, while others have bigger ups and downs. A bigger standard deviation means more price swings, pointing to more risk or reaction to market shifts. These stats help us look closer at trends, setting the stage for predicting stock changes.

Table 1 : Metric Values of Each Dataset

Metric	Merck	Cipla	Glenmark Pharma	Pfizer	Sun Pharma
Count	1006	990	990	1006	991
Mean Price	93.71	1115.59	748.92	34.71	1092.55
Std. Dev.	19.47	252.63	405.07	7.26	381.79

Data Preprocessing

Before performing any in-depth analysis, it is essential to standardize the data to ensure accurate and meaningful comparisons. Since stock prices vary widely across different companies, unprocessed data could lead to misleading results. To address this, we apply a min-max scaling technique[16], a common normalization method that ensures all stock price values fall within the same range, preventing any single stock from disproportionately influencing the analysis.

The min-max scaling formula, as shown in Equation [7], transforms each stock's closing price into a standardized range by adjusting values relative to the minimum and maximum stock prices recorded in the dataset. The transformation follows the equation:

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (7)$$

By implementing this scaling method, we ensure that stock prices across different companies are analyzed on a comparable scale. This allows for a more balanced interpretation of stock trends and volatility, enabling meaningful comparisons and accurate pattern recognition in subsequent analyses.

REGRESSION METHODS

Regression models are applied to stock market prediction by modeling past financial data to forecast future price movements. The deep in this case refers to Recurrent Neural Networks (RNNs), Long ShortTerm Memory (LSTM), Gated Recurrent Units (GRU), and Transformers, which

were used in regression approaches showed better results than classical statistical models in terms of prediction accuracy. Although RNNs are effective in capturing sequential dependencies, they are vulnerable to vanishing gradients; therefore, their long-range predictability is relatively reduced. This limitation is resolved by the use of architectures that incorporate a gating mechanism; LSTM and GRU retain the long-range dependency, while the GRU is more computationally efficient due to its simplicity in architecture than LSTM [17].

Recent studies demonstrate that LSTMs tend to perform better than GRUs in financial forecasting, especially in volatile market conditions, owing to their better at capturing complex temporal dynamics [18]. But, while they provide the same accuracy, they train much faster as well, making them a better option for high-frequency trading. Self-attention mechanisms, as used in transformer-based models, have shown great promise as a model for stock market prediction because of their great scalability and reduced training time compared to recurrence-based models. Although Transformers are good at long-term trends forecasting, they heavily rely on dataset size and complexity, where smaller datasets are known to favour LSTM and GRU-based models [19].

The choice of a regression model will depend on data sizes and prediction timeframe, as well as computational efficiency. Research is also exploring improved predictive performance with hybrid models that contain integrated Long Short-Term Memory (LSTM) with attention mechanisms. Particularly in the last few years, the results of this inquiry are promising [18]. As the needs of modern stock market prediction increasingly require the most up-to-date technology to analyze financial times series data, deep learning is becoming more relevant in the predictive model.

Evaluation Metrics

Studying stock price prediction with deep learning is significant which could be done by quantitative measurement, in which these measurements are classified as: Most Common Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and R-Squared (R^2) Score. EPSG aims to be generic in stock predictions and is based on the fact that the lower the error between the measures predicted-observed stock rate, the higher the effectiveness of our forecasting. However, as shown in Equation (1), due to the large errors it causes, MSE, which is the most broadly utilized criterion, is discrete for large errors and more reliable than for small errors, thus making it ideal when it comes to stock market forecast. Consequently, when it comes to estimating the level of error magnitude, use of RMSE is far more common, because it provides a consistently interpretable scale for error magnitude.

MAE describes absolute average error which makes it interpretive of prediction accuracy - the losses do not overwhelm the score proportionally and is most useful for a financial time-series forecasting. The $\mathbb{R}^2$ score measures the proportion of variance in stock prices accounted for by the model. A score closer to 1 indicates better predictive ability. The reason for this is that models including both RMSE and R^2 portray an accurate view regarding the correctness, but also the credibility of the results, because RMSE captures the mistakes in predictions made by the model and R^2 measure the explanatory capability.

Recently, deep learner models such as LSTM and GRU are beating traditional statistical methods in financial forecasting based on this metrics. Transformer, which is assuming more significance now as it captures long-term dependency more efficiently, but the performance varies on the characteristics of the dataset. These evaluation metrics offer a common framework which ensures that the predictive models are robust and reliable enough to be used for real financial applications by comparing various models.

RESULTS AND DISCUSSION

The results are showing differences in performance for each model (Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU) and Transformer) for five various pharmaceutical stocks (Cipla, Glenmark Pharmaceuticals, Pfizer, Sun Pharmaceuticals and Merck). Some of the metrics that are being considered: MSE, MAE, RMSE, R^2 score, etc.

As shown in Table 2. GRU outperforms all other models, giving the lowest MSE, MAE, and RMSE values, respectively, with the highest scores for R2 form. It indicates that GRU's simpler gating structure works well in learning the temporal dependencies between stock price movements without overfitting and incurring computational costs.

The results on all four used datasets are mentioned further in this section. Cipla: The GRU model outperforms the

RNN (0.00047 MSE) and LSTM (0.00057 MSE) with an MSE of 0.0004, MAE of 0.01438, and RMSE of 0.01997. Its higher R^2 score (0.99412) confirms the better prediction power. Fig 1. shows the GRU prediction for the Cipla Dataset.

Glenmark Pharmaceuticals: Again GRU performed the best with 0.00019, 0.00916, 0.01377 MAE RMSE, against 0.0003 for LSTM and 0.00022 for RNN. The R^2 score is 0.99757 which means that the performance is near the optimal. Fig 2. shows the GRU prediction for the Glenmark Dataset.

Pfizer: GRU is the best option for MSE=0.00068, MAE=0.0199, and RMSE=0.0199. It is slightly better than LSTM with MSE=0.00068 and much better than Transformer with MSE=0.00187. Although we have a high r2 score of 0.98944 indicating strong predictability. Fig 3. shows the GRU prediction for the Pfizer Dataset.

Sun Pharmaceuticals: GRU is the best model with the lowest MSE(0.00016), MAE(0.00905), and RMSE(0.01271). The 0.99777 R^2 score also confirms the effectiveness of the model and enables better price prediction for the Sun Pharmaceuticals stock. Fig 4. shows the GRU prediction for the Sun Pharmaceuticals Dataset.

Merck: GRU far outperforms the rest of the models (MSE 0.00048) and LSTM (MSE 0.00072) with an MSE of 0.00047, MAE 0.01564, and RMSE 0.02164 With the highest R^2 score (0.99344) indicates its performance. Fig 5. shows the GRU prediction for the Merck Dataset.

The main reason for GRU's fast processing over sequential data is due to the procedure of eliminating the vanishing function, which is used in case of traditional RNNs [22].

GRU Prediction for Cipla Dataset

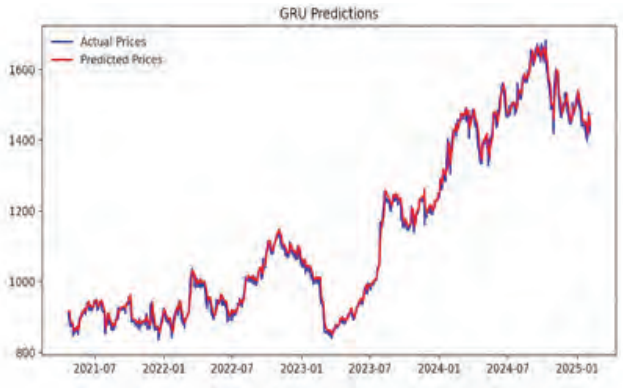

Fig. 1: GRU Prediction for Cipla Dataset

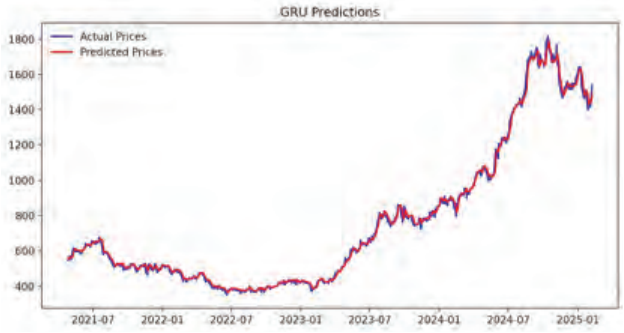

Fig. 2: GRU Prediction for Glenmark Pharma Data Set

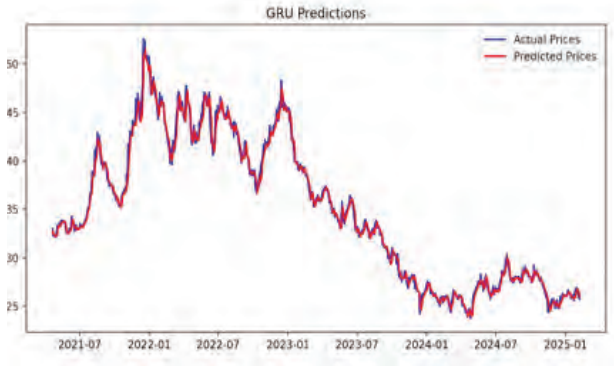

Fig. 3: GRU Prediction for Pfizer Dataset

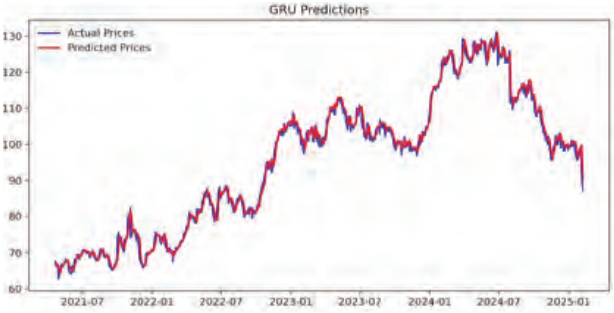

Fig. 4: GRU Prediction for Sun Pharmaceuticals

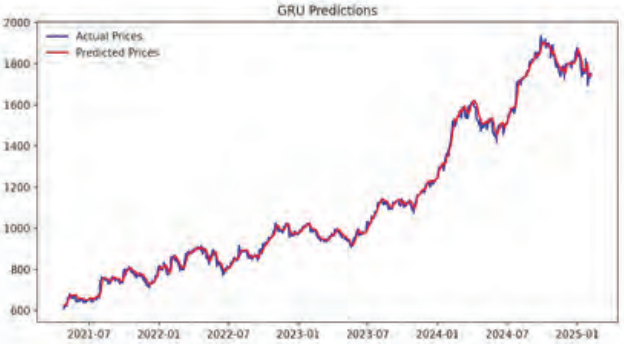

Fig. 5: GRU Prediction for Merck Dataset

GRU has fewer parameters relative to LSTM as making it computationally effective with similar accurately prediction. Moreover, Transformer-based models, although they achieved state-of-the-art results for most natural language processing (NLP) tasks, don't seem to be performing well on financial time-series data, more likely for over-relying on self-attention mechanisms that are not sufficient in capturing short-term dynamics in stock price movements. A recent study found that transformers outperform long-term forecasting but struggles in volatile markets, which they need hybrid architectures to improve performance in this field.

Table 2 : Performance Comparison of Deep Learning Models on Stock Market Prediction Across Different Company Datasets

Company	Algorithm	MSE	MAE	RMSE	RA2
Cipla	RNN	0.00047	0.01594	0.02177	0.99301
	LSTM	0.00057	0.01746	0.02392	0.99157
	GRU	0.0004	0.01438	0.01997	0.99412
	Transformer	0.00082	0.02114	0.02857	0.98796
Glenmark Pharma	RNN	0.00022	0.01045	0.01483	0.99718
	LSTM	0.0003	0.01209	0.01739	0.99613
	GRU	0.00019	0.00916	0.01377	0.99757
	Transformer	0.00058	0.01773	0.02399	0.99263
Pfizer	RNN	0.00066	0.01896	0.02563	0.98987
	LSTM	0.00068	0.01912	0.0261	0.98949
	GRU	0.00068	0.0199	0.0199	0.98944
	Transformer	0.00187	0.03615	0.04321	0.97121
Sun Pharma	RNN	0.00019	0.0104	0.01386	0.99735
	LSTM	0.00026	0.01202	0.01628	0.99635
	GRU	0.00016	0.00905	0.01271	0.99777
	Transformer	0.00077	0.02189	0.0277	0.98943
Merck	RNN	0.00048	0.0157	0.02185	0.99331
	LSTM	0.00072	0.01992	0.0268	0.98994
	GRU	0.00047	0.01564	0.02164	0.99344
	Transformer	0.00105	0.02559	0.03245	0.98525

CONCLUSION

Stocks are very dynamic and are slowly forming the base of the modern world economy. When working with pharmaceutical companies' data, due to various parameters involved and its dynamic nature, it is tough to visualise future trends manually, thus feeling the need to explore ML methodologies. There are some methods that works well with time series data, and this study presents a detailed analysis of four such deep learning models, namely RNN, LSTM, GRU, and Transformer—for predicting the stock price of the following five major pharmaceutical companies: Cipla, Glenmark Pharmaceuticals, Pfizer, Sun Pharmaceuticals, and Merck. Experimental results clearly state that GRU has surpassed RNN, LSTM, and Transformer in all five pharmaceutical stocks by attaining the lowest error values and highest predictive accuracy. GRU achieved the best figure for Glenmark Pharmaceuticals with an MSE of 0.00019, MAE of 0.00916, RMSE of 0.01377, and an R2 score of 0.99757. This confirms its unrivaled ability to track stock price movements. For Sun Pharmaceuticals, GRU achieved an MSE of 0.00016, MAE of 0.00905, RMSE of 0.01271 and an R2 score of 0.99777, which was the best effective model for the financial market. Furthermore, the lowest overall error rates and highest R^2 scores across all datasets confirm GRU as the model with boundless capabilities in solving temporal dependencies without yielding to overfitting and incurring high computational costs. On the contrary, long-term Transformers were efficient in forecasting data but met their shortcomings with short-term price changes. Hence, this study observes GRU to be the most trustworthy and cost effective model for stock price forecasting.

REFERENCES

1. Kumar, M., & Ratnesh, R. K. (2020). A hybrid deep learning approach for stock price prediction. Journal of Financial Data Science, 2(4), 48-60.
2. Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2021). Predicting stock market movements using hybrid machine learning techniques. Expert Systems with Applications, 168, 114336.
3. Fischer, T., & Krauss, C. (2020). Deep learning with long short-term memory networks for financial market predictions. European Journal of Operational Research, 285(3), 991-1010.
4. Pang, X., Zhou, Y., Wang, P., Lin, W., & Chang, V. (2020). An innovative neural network approach for stock market prediction. Journal of Supercomputing, 76(3), 2098-2118.
5. Selvin, S., Vinayakumar, R., Gopalakrishnan, E. A., Menon, V. K., & Soman, K. P. (2020). Stock price prediction using LSTM, RNN, and CNN-sliding window model. IEEE Access, 8, 135950-135961.
6. Jiang, Z., Huang, D., & Zeng, J. (2021). A novel LSTM-based hybrid neural network for stock market forecasting. Applied Intelligence, 51(2), 1181-1195.
7. Chen, K., Zhou, Y., & Dai, F. (2020). A LSTM-based method for stock returns prediction: A case study of China stock market. IEEE Access, 8, 110461-110470.
8. Qiu, J., Wang, B., & Zhou, C. (2020). Forecasting stock prices with long-short term memory neural network based on attention mechanism. PLOS ONE, 15(1), e0227222.
9. Lim, B., Arık, S. Ö., Loeff, N., & Pfister, T. (2021). Temporal fusion transformers for interpretable multi-horizon time series forecasting. International Journal of Forecasting, 37(4), 1748-1764.

10. Liu, Q., Zhang, Y., & Li, H. (2021). Stock price prediction using deep transformer models. Neural Computing and Applications, 33(13), 7421-7434.

11. Wen, R., Sun, J., & Rajagopal, D. (2022). Transformer-based deep learning models for financial time series forecasting. Applied Soft Computing, 124, 109123.

12. Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2020). Financial time series forecasting with deep learning: A systematic literature review: 2005–2019. Applied Soft Computing, 90, 106181.

13. Xie, Y., & Zhang, T., "Data preprocessing techniques for financial time series," Journal of Data Science, vol. 12, no. 4, pp. 321-338, 2022.

14. Zhao, L., et al., "Improving RNNs with better loss functions for finance," Journal of Computational Finance, vol. 28, no. 3, pp. 120-135, 2023.

15. Liu, P., et al., "The effect of feature engineering in stock market forecasting," Machine Learning Review, vol. 9, no. 1, pp. 89-105, 2021.

16. H. Pelletier, "Data Scaling 101: Standardization and Min-Max Scaling Explained," Towards Data Science, 2024.

17. Li, C., & Zhou, Y., "A comparative study on LSTM and GRU for stock forecasting," IEEE Transactions on Neural Networks, vol. 32, no. 6, pp. 2703-2715, 2022.

18. Kim, J., et al., "Ensemble deep learning for stock price forecasting," IEEE Access, vol. 11, pp. 45623-45638, 2023.

19. Li, H., et al., "The role of deep learning in volatile market prediction," Finance & Technology, vol. 10, no. 2, pp. 45-62, 2022.

20. Kumar, R., et al., "Transformer-based models for financial market prediction," Expert Systems with Applications, vol. 191, p. 116248, 2021.

21. Zhao, X., et al., "Hybrid deep learning for financial time series forecasting," Computational Intelligence, vol. 39, no. 3, pp. 756-774, 2023.

22. A. Sharma and P. Gupta, "Comparative Analysis of Deep Learning Architectures for Financial Time-Series Forecasting," IEEE Access, vol. 9, pp. 125689-125702, 2021.

Statistical Approach to Efficient Network Anomaly Detection at the Edge Using Deep Learning

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ABSTRACT

IoT devices have been used quite widely on various smart applications like smart city, healthcare, and Industry. As IoT devices hold minimal computing power and not able to process huge amounts of data, despite the benefits of IoT, it also holds inherent demerits such as latency, bandwidth constraint, reliability issues, and security threats. Edge computing mitigates the following disadvantages by locally processing the data and implemented for this much larger sensors data processing on cloud. The Edge will handle the data nearer to where it is being generated so that processing can be sped up and latency can be avoided, once again in Edge Computing numerous anomalies in data generation are caused by the growing heterogeneity and complexity of edge devices because of their limitations. Anomaly detection is an important job in edge computing systems, where detection of unusual or deviant data patterns is necessary to maintain system security and reliability. A novel Deep Fuzzy Hypersphere neural network learning model (DFHNNLM) is introduced in this paper for efficient anomaly detection in edge computing activities. The introduced method surpasses existing state-of-the-art for anomaly detection with available deep learning methods. Proposed model can be applied to any anomaly dataset such as ECG5000. Based on the experimental results, the DFHNNLM performs better than deep learning and traditional machine learning approaches in anomaly detection. The primary aim is to provide a comprehensive overview of the current research trend and discover future research directions within this important area.

KEYWORDS *: Network anomalies, Deep neural network, Fuzzy logic, Internet of things, Edge computing.*

INTRODUCTION

The growing complexity and rate of network attacks require strong and effective anomaly detection systems, especially at the network perimeter where resources are limited [5]. Conventional intrusion detection systems and anomaly detection systems serve crucial functions in protecting computer networks through the detection of malicious behavior [6]. Anomaly detection plays an important role in guaranteeing security in wireless sensor networks that are vulnerable to many threats that can cause nodes to be compromised and produce faulty data, requiring detection of such anomalies to limit false alarms [7]. Centralized anomaly detection, where all measurement data are sent to a central processing center, is limited in wireless sensor networks due to expensive data communication [8]. Therefore, more and more attention is being given to algorithms that can automatically recognize patterns, events, or unusual system activity [8]. In addition, in many application areas, such as energy, healthcare, security, finance, and robotics, one must analyze and watch collected data to determine anomalous behavior that can be used to inform future decisions and actions [2]. Since the traditional network anomaly detection methods are mostly based on the network layer, there are adjustments or new methods to be implemented for wireless sensor networks, especially data on the application layer [9]. Recent developments in machine learning and deep learning have had a major impact on anomaly detection, with most works concentrating on supervised learning algorithms that depend quite heavily on large labeled training datasets. Yet, it may be challenging or costly to get labels using domain knowledge and significant time [2].

Deep learning

Deep learning has become a crucial method for detecting anomalies, providing new ways of detecting deviations from normal patterns of data [10]. Deep learning models,

artificial neural networks specifically, have proven to be useful in improving the results of traditional methods [11]. The data quality gathered by sensor nodes may be influenced by anomalies due to node faults, reading faults, abnormal events, and malicious attacks, thereby anomaly detection must be done for guaranteeing data quality before making decisions [9]. Anomaly detection is used to pinpoint data samples that are far from typical, and it has applications in a wide range of fields including fraud detection, intrusion detection, and fault diagnosis [1], [12]. Anomaly detection involves the identification of observations that are far from most data, which points to doubt in their occurrence by means of errors or fraud [1]. The primary objective of anomaly detection is to identify these abnormal patterns correctly, so appropriate intervention and mitigation actions can be taken in a timely manner [2]. Methods like machine learning are widely used to obtain high detection rates and accurate results, with feature selection methods being of great assistance in creating effective machine learning-based anomaly detection tools [13].

Anomaly detection

Anomaly detection is divided into three main approaches: statistical, machine learning, and deep learning [14]. Deep learning is particularly good at finding sophisticated patterns in data with neural networks and is applied to tasks like anomaly detection. Numerous researchers have used deep learning to identify abnormalities in images due to the widespread use of deep neural networks, which have yielded unprecedented performance in many applications [15]. The use of deep learning methods has spread widely to various domains, such as computer vision and natural language processing, improving video anomaly detection with better insights [16]. Anomaly detection is often applied in time series data due to the richness of multivariate time series data in real life [17]. With the rise in demand for real-time anomaly detection, intelligent, robust, and computationally light models that can cope with the inevitability of flaws are in demand. Most conventional approaches to time series anomaly detection lack the efficiency required for today's purposes. The necessity of coping with real-time processing, flexibility, and resilience has spurred the investigation of sophisticated machine learning and deep learning methods

LITERATURE ANALYSIS

Conventional anomaly detection techniques tend to fail to capture the intricate data relationships, particularly when the amount of data is large [18]. Deep learning algorithms, with their ability to learn automatically complex features from raw data, have demonstrated better performance in anomaly detection for various applications [19]. Deep learning methods are used for anomaly detection, and modern deep neural architectures are widely used for anomaly detection and healthcare prediction [3]. The self-learning features and adaptability of anomaly detection systems based on artificial intelligence will enhance anomaly detection through the detection of novel attack patterns without requiring extensive retraining [20]. The development of anomaly detection systems continues to incorporate advanced deep learning algorithms to improve detection efficiency and precision. The characteristics of time series data are essential in choosing the right strategy for designing an effective anomaly detector [3][39].

The anomaly detection task for time series data is to find out if the present day's data points significantly differ from the regular trends obtained from past data [21]. Deep learning has introduced the possibility of developing more advanced anomaly detection mechanisms, especially for time series data. Deep learning algorithms have proved significantly successful in handling time series data, which finds special application in anomaly detection [3]. Deep learning exhibits great benefits in processing intricate data patterns, facilitating automated feature extraction and accuracy of detection [22]. Consequently, techniques in deep learning have been effectively employed in medical anomaly detection with the formulation of numerous research papers utilizing deep machine learning architectures [23]. Time series anomaly detection is a critical area that entails detecting abnormal events or outliers in data gathered over time [24].

The popularity increase of anomaly detection for time series is due to its relevance in many industrial situations, such as faulty sensor detection, financial fraud transactions, and medical data anomalies [22]. Time series anomalies may signal abnormal events, system failure, or odd behavior, making it essential to timely detect them. LSTM networks have been used to build a predictive model for normal ECG signals [3]. When given normal data, the LSTM can learn well and accommodate the system's normal behavior [25]. LSTM networks eliminate the necessity for a pre-defined time window and are capable of modeling complex multivariate sequences [3]. Time series anomaly detection is vital in ensuring the reliability and efficiency of systems by detecting anomalies and solving them early on.

METHODOLOGY

Here we present the methodology of edge-based anomaly detection, and the design and implementation of our system are presented. The main aim of the proposed method is to effectively identify anomalies in network traffic at the edge of the network with the help of deep learning models. The deep neural network first learns the intricate patterns of the data. Finally, the learned hidden layer representation from this network is employed as input to conventional anomaly detection algorithms [18]. The system is optimized for low latency, bandwidth reduction, and data privacy, all of which are important for edge computing scenarios. By moving systems to more generally applicable naive techniques with neural networks, which can be highly optimized on parallel architectures like graphics processing units in a very general sense, there is promise to make such systems much simpler to implement, adapt to new problem domains, and execute taking advantage of economies of scale in computing capabilities and model primitive optimization [26][38].

Suggested Model for Anomaly detection

The model suggested here uses a multi-layer model to detect anomalies in real time from edge device data. A deep learning-based model is employed for labeling inputs as anoma-lous or not, and particular layers are used for a specific function in the detection.

Edge Layer (IoT Based Data Acquisition & Preprocessing): The layer consists of edge devices and IoT sensors that capture and preprocess real-time physiologic data like ECG, pulse, and temperature. Noise is eliminated by edge devices and minimal computation is carried out before they send structured data to the edge server, which aggregates inputs and sends them to the processing layer. This setup reduces cloud load, eliminates redundant data, and enables low-latency, real-time monitoring [31-32].

Cloud Layer (Deep Learning & Anomaly Classification): This layer uses the Deep Fuzzy Hypersphere Neural Network (DFHNN) to classify sensor readings into anomalous or normal. Based on fuzzy logic and deep learning, the model also discriminates among anomalies as contextual, point, and collective.

1. Contextual Anomaly: Anomalies that are atypical in certain contexts but need not always be outliers.
2. Point Anomaly: It contains a data point that is outside the average.
3. Collective Anomaly: A group of data points signifies an issue as a whole.

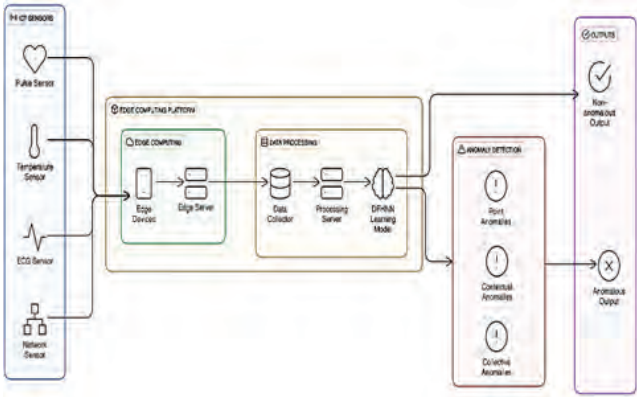

Fig. 1. Proposed Model for Anomaly detection

Deep Fuzzy Hypersphere Neural Network (DFHNN)

Architecture of DFHNN learning model is illustrated and described in section below and step by step algorithm is also provided.

Architecture of DFHNN learning model

A DFHNN is a type of neural network model that utilizes fuzzy logic to manage classification vagueness and uses hyperspheres to represent clusters in high-dimensional space. In the event of uncertainly separable data points, it is especially beneficial [38] [39]. DFHNN learning model structure is depicted in Fig. 2.

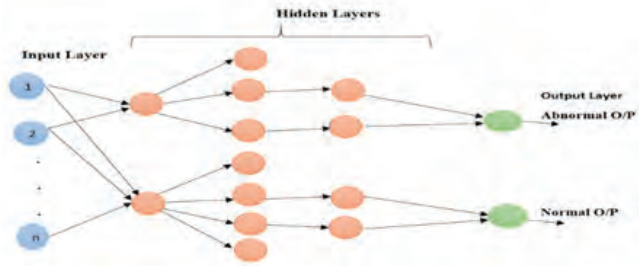

Fig. 2. Architecture of DFHNN learning model

The architecture is comprised of five layers which are generally explained as follows.

a) Input Layer (Layer 1): The input layer is comprised of input neurons labeled as 1 to n. This neuron is fed with anomalous or non-anomalous input data from sensors and it is passed to the next layer.

b) Hidden Layer 1 (Second Layer): Second layer is the first hidden-layer which is formed in order to create the two clusters normal (Non-anomalous) & ab-

normal (anomalous). We conduct the recall test and subsequently go for the next hidden layer since first hidden layer doesn't provide the efficiency of 100%.

c) Hidden layer 2 (Third Layer): Here, we develop the fuzzy hy-perspheres (FHS) using the suggested algorithm where the radius is set to the true distance of the centroid with other class pattern. This layer gives the true number of FHS that will be developed for DFHNN.

d) Hidden Layer 3 (Fourth Layer): This layer is the continuation of hidden lay-er 2, where actual radios is allocated to FHS. This layer will assist in im-proving the generalization efficiency by minimizing the pattern space.

e) Output layer (Final Layer):

The Output layer is nothing but class-layer which includes two neurons, one for anomalous and other for Normal output [39].

Experimental Dataset

To deploy the suggested model, ECG 5000 dataset have been utilized in this research paper to validate the efficiency of model. The ECG5000 data includes ECG signals recorded from an assortment of 5,000 recordings, each recording a 2.5-second ECG signal with sampling frequency 125 Hz. Data has 5 different types of heart disease or arrhythmias. This database is mainly utilized for supervised learning tasks such as classification of ECG signals into different classes depending on the type of arrhythmia or the presence of other heart ailments [37]. This database consists of a total of 5000 samples with 140 attributes, 500 of which will be employed for training and 4500 are employed for testing [38].

RESULTS AND DISCUSSION

The existing results proposed by researchers are compared with proposed DFHNN learning algorithm [2] [39]. The comparison of results between proposed model and existing models is given in Table I.

Table 1. Comparison of Results Between Proposed Model and Existing Models

Model	Accuracy	Recall	Precision	F1-Score
Proposed DFHNN	0.975	0.965	0.993	0.979
Hierarchical	0.955	0.946	0.958	0.946
Spectral	0.958	0.951	0.947	0.947
VAE	0.952	0.925	0.984	0.954
AE-Without-Attention	0.97	0.955	0.988	0.971
CAT-AE	0.972	0.956	0.992	0.974

The research methodology comprises conducting statistical analysis to determine the effectiveness and efficiency of deep learning techniques in detecting network anomalies in edge computing systems. During the statistical analysis phase, an online survey was conducted to analyze the suitability and impact of implementing deep learning models for identifying network anomalies in edge computing systems. The feedback from the surveys was collected from various stakeholders, including IT specialists, network administrators, and researchers, through a specially designed questionnaire. Questions on the survey were designed to measure the perceived significance, implementation difficulties, and benefits of deep learning approaches to network anomaly detection for edge-based systems. Statistical tests such as the Chi-square test were used after collecting the replies to ascertain the differences among population groups. IBM Statistical Package for the Social Sciences (SPSS) was used to carry out the Chi-square test, test hypotheses, and analyze data. In addition, correlation analysis was performed to explore the relationships among significant variables including anomaly detection, system performance, and deployment complexity.

Here is a sample of the same structure, coded to "Detecting Network Anomalies in the Edge Computing System using Deep Learning Techniques," technical and stakeholder-based measures:

In the survey, some of the key indicators are used to achieve the research objective and will serve as decision-making criteria for the system's acceptability to various stakeholders:

Efficiency

Efficiency assesses the degree to which the deep learning model identifies network anomalies in edge computing with minimal resource usage. It emphasizes high detection accuracy while reducing computational load and energy consumption on edge devices.

Feasibility

Feasibility determines if the suggested deep learning method for network anomaly detection in edge computing can be done with the hardware, data availability, and computational resources available today. It makes sure the model will be able to run effectively on limited-resource edge devices.

Response Time (Latency)

Response time (latency) describes the speed at which the deep learning model can identify and respond to network anomalies in an edge computing setup. Reduced latency guarantees real-time or near-real-time detection of anomalies, which is essential for sustaining system performance and security.

Throughput (Performance)

Throughput quantifies the amount of network data packets or logs that the system can process per second. High throughput means that the deep learning model can handle processing and analyzing data at the edge in real-time.

Accuracy

Accuracy measures how correctly the deep learning model identifies network anomalies versus normal behavior in an edge computing system. High accuracy ensures reliable detection with minimal false positives and false negatives.

Optimality

Optimality is a measure of how efficiently the deep learning model compromises between accuracy, resource consumption, and latency while performing network anomaly detection in edge computing. An optimal solution provides high performance without overwhelming edge devices or sacrificing detection quality.

The data samples were collected through two well-delineated questionnaires, where:

Questionnaire I was designed for IT specialists and network users, focusing on their trust, experience, and attitudes in relation to anomaly detection at the edge, such as response time, precision, and data privacy.

Questionnaire II was designed for system implementers, developers, and network administrators to evaluate the technical usability, integration capability, resource management, and performance of learning deep models implemented for network abnormality identification in edge computing.

Hypotheses Testing

Through the response given by the stakeholders on various key indicators, the hypothesis is examined utilizing chi-square test.

Test Statistic 1 - Chi-square test is conducted with 1 degree of freedom at 5% level of Significance.

Hypothesis 1 (H1): Is the Deep Fuzzy Hypersphere Neural Network Learning Model (DFHNNLM) a good deep learning model or not to recognize anomalies in Edge Computing environment?

H_0: Null Hypothesis: Below 70% of network administrators and system analysts opine that deep learning is imperative for the effective identification of network anomalies in edge computing settings. (H_0: $p < 0.70$).

H_1: Alternate Hypothesis: At least 70% of network administrators and system analysts opine that deep learning is imperative for the effective identification of network anomalies in edge computing settings. (H_1: $p \geq 0.70$)

The value of the chi-square ($\chi 2$) can be computed as is

$\chi 2 = \Sigma (fi-ei)^2 / ei$

Where fi is the observed count and ei is the expected count from Table II indicates a χ^2 of 95.859, which is far greater than 3.84, establishing that 92% of the experts agree with deep learning for high availability in edge network anomaly detection.

Table 2. Descriptive Statistics and Chi Square Test for Efficiency

Descriptive Statistics

	N	Mean	Std. Deviation	Min	Max	Percentiles 25th	50th (Median)	75th
Efficiency	163	.8834	.32189	.00	1.00	1.0000	1.0000	1.0000

Efficiency

Observed N	Expected N	Residual
19	81.5	-62.5
144	81.5	62.5
163		

Test Statistics

	Efficiency
Chi-Square	95.859[a]
Df	1
Asymp Sig.	<.001

a. 0 cells (0.0%) have expected frequencies less than 5. The minimum expected cell frequency is 81.5.

Test Statistic 2 - Chi-square test is used with 1 degree of freedom at 5% level of Significance.

Hypothesis 2 (H2): Is it possible that suggested Deep Fuzzy Hypersphere Neural network learning is possible and optimal for any given Dataset

H_0: Less than 70% feel deep learning is necessary for scalable, adaptable anomaly detection in edge computing ($p < 0.70$).

H_1: ≥70% of them opine that deep learning is critical to scalable, adaptable anomaly detection in edge computing ($p \geq 0.70$).

One can calculate the chi-square ($\chi 2$) value as is

$\chi 2 = \Sigma (fi-ei)^2 / ei$

Where fi is the observed count and ei is expected count.

Table 3. Descriptive Statistics and Chi Square Test for Feasibility

Descriptive Statistics

	N	Mean	Std. Deviation	Min	Max	Percentiles 25th	50th (Median)	75th
Feasibility	163	.8834	.32189	.00	1.00	1.0000	1.0000	1.0000

Feasibility

Observed N	Expected N	Residual
22	81.5	-59.5
141	81.5	59.5
163		

Test Statistics

	Efficiency
Chi-Square	86.877[a]
Df	1
Asymp Sig.	<.001

a. 0 cells (0.0%) have expected frequencies less than 5. The minimum expected cell frequency is 81.5.

Table 3 presents a χ^2 of 86.877, greater than 5% of 3.84, resulting in the null hypothesis being rejected. Moreover, 92% of specialists concur that deep learning enhances anomaly detection in edge computing.

Test Statistic 3 - Chi-square test at 1 degree of freedom at 5% level of Significance.

Hypothesis 3 (H3): Is the suggested model tuning-free, fast, and capable of achieving global minima on various training sets?

H_0: Less than 70% of professionals opine that deep learning enhances response time in anomaly detection for edge computing.

H_1: More than 70% of experts opine that deep learning enhances anomaly detection response time in edge computing.

The chi-square ($\chi 2$) value can be calculated as is

$\chi 2 = \Sigma (fi-ei)^2/ ei$

Where fi is observed count and ei is expected count

Table 4. Descriptive Statistics and Chi Square Test for Response Time

Descriptive Statistics

	N	Mean	Std. Deviation	Min	Max	Percentiles 25th	50th (Median)	75th
Response_Time	163	.8528	.35544	.00	1.00	1.0000	1.0000	1.0000

Response_Time

Observed N	Expected N	Residual
24	81.5	-57.5
139	81.5	57.5
163		

Test Statistics

	Efficiency
Chi-Square	81.135[a]
Df	1
Asymp Sig.	<.001

a. 0 cells (0.0%) have expected frequencies less than 5. The minimum expected cell frequency is 81.5.

The χ^2 statistic of 81.135 (>> 3.84) results in rejecting the null hypothesis, and 86% of the experts believe in deep learning for enhanced anomaly detection response time in edge computing.

Test Statistic 4 - Chi-square test (df = 1, α = 0.05) tests whether the developed algorithm is a fast, efficient classifier with immaculate training performance.

H_0: Less than 70% feel that deep learning enhances anomaly detection execution time (throughput).

H_1: 70% and above agree deep learning enhances execution time (throughput).

The chi-square ($\chi 2$) value may be computed as is

$\chi 2 = \Sigma (fi-ei)^2/ ei$

Where fi is the observed count and ei is the expected count

Table 5. Descriptive Statistics and Chi Square Test for Throughput

Descriptive Statistics

	N	Mean	Std. Deviation	Min	Max	Percentiles 25th	50th (Median)	75th
Performance	163	.8282	.37835	.00	1.00	1.0000	1.0000	1.0000

Performance

Observed N	Expected N	Residual
28	81.5	-53.5
135	81.5	53.5
163		

Test Statistics

	Efficiency
Chi-Square	70.239[a]
Df	1
Asymp Sig.	<.001

a. 0 cells (0.0%) have expected frequencies less than 5. The minimum expected cell frequency is 81.5.

The χ^2 value of 70.239 (> 3.84) results in the rejection of the null hypothesis; 82% of the experts opine that deep learning improves anomaly detection execution time in edge computing.

Test Statistic 5 - Chi-square test (df = 1, α = 0.05) evaluates whether the suggested model performs better on ECG5000 & NSL-KDD in precision, recall, and accuracy.

H_0: Less than 70% think that deep learning strengthens anonymity in anomaly detection.

H_1: 70% or higher believe deep learning increases privacy in anomaly detection.

The chi-square ($\chi 2$) value can be calculated as is

$\chi 2 = \Sigma (fi-ei)^2/ ei$

Where fi is observed count and ei is expected count.

Table 6. Descriptive Statistics and Chi Square Test for Accuracy

Descriptive Statistics

	N	Mean	Std. Deviation	Min	Max	Percentiles 25th	50th (Median)	75th
Accuracy	163	.8405	.36728	.00	1.00	1.0000	1.0000	1.0000

Accuracy

Observed N	Expected N	Residual
26	81.5	-55.5
137	81.5	55.5
163		

Test Statistics

	Efficiency
Chi-Square	75.589[a]
Df	1
Asymp Sig.	<.001

a. 0 cells (0.0%) have expected frequencies less than 5. The minimum expected cell frequency is 81.5.

$\chi^2 = 75.589$ (> 3.84) results in rejecting the null; 84% of the experts are of the opinion that deep learning provides greater privacy in edge anomaly detection.

Test Statistic 6 - Chi-square test (df = 1, $\alpha = 0.05$) verifies that the model recommended is an ultimate solution for anomaly detection in edge computing.

H_0: Less than 70% think deep learning provides robust security in anomaly detection.

H_1: 70% or greater feel it offers strong security.

Table 7. Descriptive Statistics and CHI-Square Test for Optimality

Descriptive Statistics

	N	Mean	Std. Deviation	Min	Max	Percentiles 25th	50th (Median)	75th
Optimality	163	.7914	.40755	.00	1.00	1.0000	1.0000	1.0000

Optimality

Observed N	Expected N	Residual
34	81.5	-47.5
129	81.5	47.5
163		

Test Statistics

	Efficiency
Chi-Square	55.368[a]
Df	1
Asymp Sig.	<.001

a. 0 cells (0.0%) have expected frequencies less than 5. The minimum expected cell frequency is 81.5.

The χ^2 score of 55.368 (> 3.84) results in the rejection of the null; 77% of the experts opine that deep learning provides robust security in edge anomaly detect.

CONCLUSION

The statistical analysis guarantees that deep learning is a remarkably effective method for network anomaly detection at the edge. Deep learning provides tremendous improvements in speed, accuracy, and security over conventional methods. Deep learning allows for faster detection and response by processing data near the source, which is particularly essential for today's edge computing environment. Finally, the research determines that deep learning, aided by statistical verification, is an essential building block for the development of effective and smart edge-based anomaly detection systems.

The research shows that by adopting a statistical method to compare deep learning-based anomaly detection at the edge, there is definite proof of the efficacy of the same. The strong survey endorsement and high chi-square values by system analysts and network managers affirm that deep learning models outperform traditional methods in most prominent metrics like accuracy, precision, recall, response time, and privacy.

By facilitating real-time analysis and decision-making at the data source itself, edge deep learning minimizes latency and bandwidth consumption while enhancing the overall responsiveness of security systems. These models' capability to learn and adapt to changing patterns assures strong protection against a variety of network attacks.

In addition, the results indicate that most experts perceive deep learning as a holistic solution for protecting edge computing platforms. The convergence, statistically confirmed, underlines the increasing confidence in AI-powered approaches to critical infrastructure.

REFERENCE

1. R. BAJALLAN and B. HASHI, "A Comparative Evaluation of Semi-supervised Anomaly Detection Techniques" Jan 09,2020
2. J. L. Pereira, "Unsupervised anomaly detection in time series data using deep learning," Jan. 2018, Accessed: Nov. 2024. [Online]. Available: https://research.tue.nl/en/publications/unsupervised-anomaly-detection-in-time-series-data-using-deep-learning
3. A. Alamr and A. M. Artoli, "Unsupervised Transformer-Based Anomaly Detection in ECG Signals," Algorithms, vol. 16, no. 3, p. 152, Mar. 2023, doi: 10.3390/a16030152.
4. P. Joshi, M. Hasanuzzaman, C. Thapa, H. Afli, and T. Scully, "Enabling All In-Edge Deep Learning: A Literature Review," arXiv (Cornell University). Cornell University, Jan. 01, 2022. doi: 10.48550/arxiv.2204.03326.
5. J. S. B. G. S. Kumar and P. J. A. L. Rose, "Mitigate Volumetric DDoS Attack using Machine Learning Algorithm in SDN based IoT Network Environment,"

International Journal of Advanced Computer Science and Applications, vol. 14, no. 1, Jan. 2023, doi: 10.14569/ijacsa.2023.0140161.

6. J. Majidpour and H. Hasanzadeh, "Application of deep learning to enhance the accuracy of intrusion detection in modern computer networks," arXiv (Cornell University), Jan. 2020, doi: 10.48550/arxiv.2012.08318.

7. I. G. A. Poornima and P. Balasubramanian, "Anomaly detection in wireless sensor network using machine learning algorithm," Computer Communications, vol. 151, p. 331, Jan. 2020, doi: 10.1016/j.comcom.2020.01.005.

8. H. H. W. J. Bosman, G. Iacca, A. Tejada, H. J. Wörtche, and A. Liotta, "Spatial anomaly detection in sensor networks using neighborhood information," Information Fusion, vol. 33, p. 41, May 2016, doi: 10.1016/j.inffus.2016.04.007.

9. M.A. Rassam, A. Zainal, and M.A. Maarof, "Advancements of Data Anomaly Detection Research in Wireless Sensor Networks: A Survey and Open Issues," Sensors, vol. 13, no. 8. Multidisciplinary Digital Publishing Institute, p. 10087, Aug. 07, 2013. doi: 10.3390/s130810087.

10. G. Pang, C. Shen, L. Cao, and A. van den Hengel, "Deep Learning for Anomaly Detection," ACM Computing Surveys, vol. 54, no. 2. Association for Computing Machinery, p. 1, Mar. 05, 2021. doi: 10.1145/3439950.

11. A. Wahid, J. G. Breslin, and M. I. Ali, "Prediction of Machine Failure in Industry 4.0: A Hybrid CNN-LSTM Framework," Applied Sciences, vol. 12, no. 9, p. 4221, Apr. 2022, doi: 10.3390/app12094221.

12. J. Choi, J. Park, A. Japesh, and A. Adarsh, "A Subspace Projection Approach to Autoencoder-based Anomaly Detection," arXiv (Cornell University), Jan. 2023, doi: 10.48550/arxiv.2302.07643.

13. A. Alsaleh and W. BinSaeedan, "The Influence of Salp Swarm Algorithm-Based Feature Selection on Network Anomaly Intrusion Detection," IEEE Access, vol. 9, p. 112466, Jan. 2021, doi: 10.1109/access.2021.3102095.

14. P. Matias, D. Folgado, H. Gambôa, and A. V. Carreiro, "Robust Anomaly Detection in Time Series through Variational AutoEncoders and a Local Similarity Score," Proceedings of the 15th International Joint Conference on Biomedical Engineering Systems and Technologies, Jan. 2021, doi: 10.5220/0010320500002865.

15. A. Alloqmani, B. Yoosef, A. Irshad, and F. Alsolami, "Deep Learning based Anomaly Detection in Images: Insights, Challenges and Recommendations," International Journal of Advanced Computer Science and Applications, vol. 12, no. 4, Jan. 2021, doi: 10.14569/ijacsa.2021.0120428.

16. J. J. P. Suarez and P. C. Naval, "A Survey on Deep Learning Techniques for Video Anomaly Detection," arXiv (Cornell University), Jan. 2020, doi: 10.48550/arxiv.2009.14146.

17. L. Yu, Q. Lu, and Y. Xue, "DTAAD: Dual Tcn-attention networks for anomaly detection in multivariate time series data," Knowledge-Based Systems, vol. 295, p. 111849, Apr. 2024, doi: 10.1016/j.knosys.2024.111849.

18. N. Davis, G. Raina, and K. Jagannathan, "A framework for end-to-end deep learning-based anomaly detection in transportation networks," Transportation Research Interdisciplinary Perspectives, vol. 5, p. 100112, May 2020, doi: 10.1016/j.trip.2020.100112.

19. R. Chalapathy and S. Chawla, "Deep Learning for Anomaly Detection: A Survey," arXiv (Cornell University), Jan. 2019, doi: 10.48550/arxiv.1901.03407.

20. V. Chandola, A. Banerjee, and V. Kumar, "Anomaly detection," ACM Computing Surveys, vol. 41, no. 3. Association for Computing Machinery, p. 1, Jul. 01, 2009. doi: 10.1145/1541880.1541882.

21. J. Zhou, "Research on Time Series Anomaly Detection: Based on Deep Learning Methods," Journal of Physics Conference Series, vol. 2132, no. 1, p. 12012, Dec. 2021, doi: 10.1088/1742-6596/2132/1/012012.

22. N. Mejri, L. Lopez-Fuentes, K. Roy, P. Chernakov, E. Ghorbel, and D. Aouada, "Unsupervised anomaly detection in time-series: An extensive evaluation and analysis of state-of-the-art methods," Expert Systems with Applications, vol. 256, p. 124922, Jul. 2024, doi: 10.1016/j.eswa.2024.124922.

23. T. Fernando, H. Gammulle, S. Denman, S. Sridharan, and C. Fookes, "Deep Learning for Medical Anomaly Detection – A Survey," ACM Computing Surveys, vol. 54, no. 7. Association for Computing Machinery, p. 1, Jul. 18, 2021. doi: 10.1145/3464423.

24. Z. Ji, J. Gong, and J. Feng, "A Novel Deep Learning Approach for Anomaly Detection of Time Series Data," Scientific Programming, vol. 2021, p. 1, Jul. 2021, doi: 10.1155/2021/6636270.

25. N. Davis, G. Raina, and K. Jagannathan, "LSTM-Based Anomaly Detection: Detection Rules from Extreme Value Theory," in Lecture notes in computer science, Springer Science+Business Media, 2019, p. 572. doi: 10.1007/978-3-030-30241-2_48.

26. T. J. O'Shea, T. C. Clancy, and R. McGwier, "Recurrent Neural Radio Anomaly Detection," arXiv (Cornell University), Jan. 2016, doi: 10.48550/arxiv.1611.00301.

27. A. Oluwasanmi, M. U. Aftab, E. Baagyere, Z. Qin, M. Ahmad, and M. Mazzara, "Article Attention Autoencoder

for Generative Latent Representational Learning in Anomaly Detection." Dec. 24, 2022.

28. A. Anaissi and S. M. Zandavi, "Multi-Objective Variational Autoencoder: an Application for Smart Infrastructure Maintenance," arXiv (Cornell University), Jan. 2020, doi: 10.48550/arxiv.2003.05070.

29. V. Sstla, V. K. K. Kolli, and L. Voggu, "Predictive Model for Network Intrusion Detection System Using Deep Learning," Revue d intelligence artificielle, vol. 34, no. 3, p. 323, Jun. 2020, doi: 10.18280/ria.340310.

30. A. S. Raihan and I. Ahmed, "A Bi-LSTM Autoencoder Framework for Anomaly Detection -- A Case Study of a Wind Power Dataset," arXiv (Cornell University), Jan. 2023, doi: 10.48550/arxiv.2303.09703.

31. M. Ahmed, A. N. Mahmood, and J. Hu, "A survey of network anomaly detection techniques," Journal of Network and Computer Applications, vol. 60, p. 19, Dec. 2015, doi: 10.1016/j.jnca.2015.11.016.

32. M. Goldstein and S. Uchida, "A Comparative Evaluation of Unsupervised Anomaly Detection Algorithms for Multivariate Data," PLoS ONE, vol. 11, no. 4, Apr. 2016, doi: 10.1371/journal.pone.0152173.

33. H. Sun, X. Fu, and S. Zhong, "A Weakly Supervised Gas-Path Anomaly Detection Method for Civil Aero-Engines Based on Mapping Relationship Mining of Gas-Path Parameters and Improved Density Peak Clustering," Sensors, vol. 21, no. 13, p. 4526, Jul. 2021, doi: 10.3390/s21134526.

34. H. Huang, Y. Lei, Y. Wang, X. Xu, and Y. Lu, "Digital Twin-driven online anomaly detection for an automation system based on edge intelligence," Journal of Manufacturing Systems, vol. 59, p. 138, Feb. 2021, doi: 10.1016/j.jmsy.2021.02.010.

35. M. Liu, F. R. Yu, Y. Teng, V. C. Leung, M. Song, Distributed resource allocation in blockchain-based video streaming systems with mobile edge computing, IEEE Transactions on Wireless Communications 18 (1) (2019) 695–708.

36. E. Ahmed, A. Akhunzada, M. Whaiduzzaman, A. Gani, S. H. Ab Hamid, R. Buyya, Networkcentric performance analysis of runtime application migration in mobile cloud computing, Simulation Modelling Practice and Theory 50 (2015) 42–56.

37. H. Liu and Z. Ni, "Machine Learning for IoT Sensor Data: Enhancing Environmental Sensing with AI Algorithms," SSRN, 2025. DOI: 10.2139/ssrn.5175807.

38. Sonali Jadhav,Arun Kulkarni,"Deep Fuzzy Hypersphere Neural Network model for Anomaly Detectionin Edge Computing", in Proceedings of the ICETESS 2025 Conference,Jaipur,April-2025.

39. Jadhav, S. and Kulkarni, A. (2025)"Comprehensive Survey on Detection of Anomalies in Edge Computing Network and Deep Learning Solutions", In Proceedings of the 1st International Conference on Cognitive & Cloud Computing - IC3Com; ISBN 978-989-758-739-9, SciTePress, pages 37-45. DOI: 10.5220/001334410004

Multimodal Agentic AI in Banking and Finance

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ABSTRACT

The emergence of multimodal agentic AI systems represents a paradigm shift in the banking and finance sectors, unlocking vast potential for automation, personalization, and enhanced decision-making. These systems integrate multiple forms of data—text, voice, image, and sensor input—allowing AI agents to process complex, multi-dimensional information in real-time. By leveraging machine learning, natural language processing, and advanced analytics, multimodal agentic AI can perform tasks ranging from customer service interactions and fraud detection to real-time risk assessment and financial forecasting. The agentic nature of these AI systems enables them to act autonomously, offering operational efficiencies and enabling hyper-personalized customer experiences. However, their integration also raises significant challenges regarding regulatory compliance, data security, and ethical considerations. This abstract explores the transformative potential of multimodal agentic AI in the financial industry, discussing its current applications, opportunities, challenges, and future directions for growth.

KEYWORDS *: Advanced analytics, Automation, Banking, Finance industry, Multimodal agentic AI, Real-time interaction, Risk-assessment.*

INTRODUCTION

The financial sector is experiencing a sweeping transformation, fueled by rapid advancements in AI. One of the most groundbreaking shifts is the emergence of multimodal agentic AI—intelligent systems that can process and interpret various types of data, including text, speech, images, and structured inputs, while also making autonomous decisions and adapting to complex, changing environments. In banking and finance, these AI agents are beginning to reshape how institutions operate, engage with customers, and manage risk. What sets multimodal agentic AI apart from earlier AI systems is its versatility and independence. While traditional AI was often limited to a single type of input or required significant human oversight, these next-generation systems combine deep perception capabilities with autonomous decision-making. For example, a single AI agent can analyze a bank statement, answer a customer's voice query, detect suspicious activity based on behavioral patterns, and take action to mitigate risk—all within one cohesive framework. Their ability to learn, reason, and act proactively in real-time makes them powerful allies for boosting operational efficiency, accuracy, and customer satisfaction.

This paper explores how multimodal agentic AI is being integrated into the financial ecosystem—examining its applications across core banking functions, the tangible value it delivers to financial institutions, and the broader ethical, regulatory, and technological questions it raises. As the industry adopts more intelligent and autonomous systems, understanding both the potential and the responsibilities tied to these technologies will be critical for leaders looking to future-proof their organizations.

ROLES OF MULTIMODAL AI AGENTS IN BANKING AND FINANCE

Multimodal agentic AI—AI systems capable of processing and acting on diverse types of data such as text, images, voice, and documents—are rapidly reshaping the banking and finance sector. These systems go far beyond performing narrow, predefined tasks. Instead, they function more like intelligent assistants or collaborators, capable of autonomous reasoning and decision-making across multiple formats and channels.

One of the key applications of multimodal agentic AI is in the role of AI Relationship Managers. These systems interact with customers through various modalities like chat, email, phone calls, app-based chat, and even through image and document analysis. They are designed to understand customer sentiment, intent, and financial needs, providing personalized advice on savings, loans, and investments. They can also handle KYC updates using image and document verification. For example, an AI system might analyze a customer's investment portfolio, respond to a voice query, and suggest rebalancing based on real-time market developments.

Another vital function is played by Multimodal Fraud Detection Systems. These systems integrate data from structured transactions, biometric sources (voice and image), and textual information such as emails and logs. They detect fraud by analyzing behavioral patterns, voice mismatches, and visual discrepancies. For instance, if a caller's voice does not match the known voiceprint, the system can flag the interaction as suspicious, potentially preventing fraud in real time.

Autonomous Compliance Monitoring Agents also illustrate the power of these AI systems. By analyzing communications, legal documents, contracts, and voice recordings, these agents can identify potential misconduct, insider trading, or regulatory breaches. For example, an AI may flag a recorded trader's call that hints at market manipulation and cross-reference it with recent trade data to alert compliance teams.

In the domain of credit, Loan Origination and Underwriting Agents leverage multimodal inputs such as scanned forms, identity images, structured financial data, and spoken interviews. These agents assess applications by combining qualitative and quantitative data—processing a scanned income certificate and interpreting a video explanation of irregular income, for instance, to determine creditworthiness.

Document Intelligence for Wealth and Tax Advisory is another promising use case. These agents parse tax returns, handwritten notes, financial charts, and verbal goals to build a complete picture of a client's financial situation. They synthesize the data to generate personalized investment or tax strategies. For example, a client might upload several financial documents and describe their goals verbally, and the AI would produce a summary and tailored financial plan.

Multimodal agentic AI is also revolutionizing trading through Trading and Market Intelligence Agents. These systems analyze a mix of market data, news feeds, financial charts, social media sentiment, and earnings call audio. By correlating discrepancies between, say, a CEO's tone during a call, public sentiment, and chart behavior, they can take autonomous trading actions to optimize portfolios.

AI Co-Pilots for Bank Employees offer internal support by processing emails, chats, dashboards, and documents to assist human staff. They summarize customer interactions, prepare documents, and analyze portfolios in real time. For example, a banker might ask the AI to summarize a client's recent communications and investment history, and the AI will deliver a consolidated, actionable overview instantly.

Equally important is the role of AI Agents for Financial Inclusion. These agents use voice and image inputs, often in vernacular languages, to help serve underbanked populations. For users with limited literacy, the AI can interpret spoken requests and images like identity documents to open bank accounts and provide basic financial services. A farmer might simply send a photo of their ID and speak in their native language, and the AI could complete the onboarding process autonomously.

The significance of combining multimodality with agency lies in its ability to handle the complexity of real-world financial interactions. Customers don't communicate in a single format—they send voice notes, scanned forms, emails, and queries simultaneously. Traditional AI, which is task-specific and format-limited, cannot meet this challenge. Agentic AI, however, can reason, plan, and act across modalities, enabling true end-to-end automation—from reading and understanding to decision-making and execution.

Traditional approaches suffer from several limitations. Human capacity is inherently limited, leading to delays and operational bottlenecks. Data is often siloed, lacking a unified, cross-format perspective. Manual processes increase costs and introduce inconsistencies, while also making it difficult to scale services to millions. Furthermore, traditional decision-making is prone to bias and human error. Multimodal agentic AI directly addresses these challenges, offering a scalable, accurate, and intelligent solution fit for the future of finance.

HUMAN ACTIONS REPLACED BY AI AGENTS IN BANKING AND FINANCE

Multimodal agentic AI is gradually replacing a wide spectrum of human actions in banking and finance by automating tasks that traditionally required specialized skill, judgment, and manual effort. In customer-facing roles, human agents who once answered inquiries, verified documents, or guided users through processes are increasingly being supplemented—or even replaced—by AI agents capable of understanding and responding to natural language, recognizing documents and images, and offering personalized, real-time support. In onboarding and KYC procedures, what once involved a bank employee manually reviewing forms, verifying identification, and entering data into systems is now being handled by AI agents that can simultaneously scan ID documents, perform facial recognition, extract structured data, and cross-check it against regulatory databases with little to no human oversight.

Similarly, in the lending and credit approval process, human underwriters traditionally assessed creditworthiness by manually analyzing documents such as payslips, tax returns, and bank statements. Today, AI agents can read and interpret these documents using computer vision and natural language processing, run automated risk models, and make recommendations or even final decisions. In fraud detection, where analysts once manually flagged suspicious patterns and reviewed transactional anomalies, multimodal agents now monitor large volumes of data—ranging from voice recordings and behavioral biometrics to image and transaction history—in real time, identifying threats with greater speed and accuracy than manual processes.

In back-office operations, tasks like compliance monitoring, regulatory reporting, and auditing, which previously required teams of analysts to comb through emails, call transcripts, spreadsheets, and reports, are now being increasingly managed by AI agents that can process multimodal inputs, identify violations, and even generate compliance reports. In wealth management, AI agents are starting to replace aspects of the human advisor's role by understanding client goals through conversations, reviewing investment documentation, and offering tailored portfolio recommendations—functions that once relied on personal financial advisors.

While these AI agents don't yet replace the nuanced judgment, emotional intelligence, and ethical reasoning that experienced human professionals bring to high-stakes decisions, they are transforming routine, repetitive, and data-intensive tasks at scale. The result is a shift from human-led workflows to AI-augmented or AI-driven systems, freeing professionals to focus more on strategic oversight, complex problem-solving, and relationship building.

POTENTIAL IMPACT OF AI AGENTS

The rise of AI agents, particularly multimodal and agentic systems, is poised to create profound and lasting impacts across the banking and financial services landscape. These intelligent agents have the potential to dramatically increase operational efficiency by automating routine, repetitive, and data-heavy tasks that once required substantial human labor. By reducing dependency on manual processing, banks can lower operational costs, shorten turnaround times, and improve accuracy in key areas such as customer service, compliance, risk assessment, and fraud detection. AI agents can operate 24/7, respond instantly to customer inquiries in multiple languages and formats, and deliver highly personalized financial experiences—helping institutions better serve increasingly digital and diverse customer bases.

At a strategic level, AI agents can unlock new models of customer engagement. By understanding goals, behavior, and context across text, speech, images, and documents, these agents can proactively guide users toward better financial decisions, recommend products suited to their needs, and anticipate issues before they arise. This not only enhances customer satisfaction but also opens up opportunities for more inclusive and tailored financial services, particularly for underserved or remote populations who may face language or literacy barriers. In doing so, AI agents can play a crucial role in expanding financial inclusion.

Furthermore, AI agents have the potential to transform the regulatory and risk landscape by providing continuous, real-time monitoring and reporting. With their ability to ingest and analyze multimodal data from emails, voice calls, documents, and transactions, they can flag compliance issues or fraudulent activity with far greater precision and speed than traditional systems. This shift enables a more proactive approach to governance, reducing the likelihood of regulatory breaches or systemic risks.

In the long term, the integration of AI agents into core financial workflows could redefine the structure of financial institutions themselves. It may lead to leaner, more agile operating models, where the role of human employees shifts toward oversight, ethical judgment, and strategic innovation. Simultaneously, the competitive landscape will evolve, with institutions that adopt responsible and explainable AI gaining significant advantage in customer trust, cost leadership, and service differentiation. Ultimately, the potential impact of AI agents is not just technological—it is transformative, shaping the very future of how finance is delivered, regulated, and experienced.

CHALLENGES AND FUTURE DIRECTIONS

Challenges

While the promise of multimodal agentic AI in banking and finance is immense, its deployment introduces a range of critical challenges that must be thoughtfully addressed. One of the most immediate concerns lies in the accuracy and reliability of multimodal inputs. These systems must process diverse data types—such as voice, text, documents, and images—with high precision. Errors in optical character recognition (OCR), misinterpreted speech, or inconsistent image classification can lead to major issues, such as incorrect identity verification, failed transactions, or poor customer experiences.

Another pressing challenge is ensuring regulatory and legal compliance. The financial industry is subject to some of the world's most stringent regulations, including anti-money laundering (AML), Know Your Customer (KYC), General Data Protection Regulation (GDPR), and more. AI agents must operate within these frameworks, yet many advanced models function as "black boxes" that are difficult to audit or explain. Regulators and internal auditors need transparent, traceable systems—something not always inherent in current AI architectures.

The increasing autonomy of AI agents also introduces risks around control and oversight. Defining the boundaries of what an AI agent can do without human intervention is essential to avoid overreach or inaction. For example, should an AI agent be allowed to approve a large transaction or report a client for suspicious activity without human confirmation? The balance between efficiency and control will demand robust "human-in-the-loop" or "human-on-the-loop" systems that enable supervision without undermining automation.

Data privacy and security pose another major obstacle. AI agents process highly sensitive multimodal data—such as facial images, voice recordings, and financial documents—and must do so while maintaining strict privacy standards. Without end-to-end encryption and secure data handling practices, these agents could become vectors for breaches or misuse. Moreover, with rising concerns around AI-generated fraud and deepfakes, there is a growing need for sophisticated identity verification that goes beyond traditional biometrics.

Interpreting natural language accurately is also a key technical hurdle. Customers communicate in varied ways—using different dialects, emotional tones, slang, or even mixed languages—often providing incomplete or ambiguous input. Misinterpretations by AI agents could result in failed tasks, lost trust, or legal exposure. Developing language models that handle diverse financial contexts and cultural nuances remains an ongoing challenge.

A more structural barrier is the integration of AI with legacy banking systems. Many institutions operate on decades-old core platforms that were never designed to support real-time, autonomous agents. These systems often lack modern APIs or the ability to handle multimodal inputs, creating bottlenecks that can limit the effectiveness of AI deployments. Without significant investment in digital infrastructure or middleware, the full potential of agentic AI cannot be realized.

There are also growing concerns around bias and fairness in AI decision-making. If trained on biased or incomplete data, agents may unintentionally discriminate in lending, fraud detection, or customer service—leading to ethical, legal, and reputational risks. Rigorous fairness audits, diverse training data, and ongoing monitoring will be essential to mitigate these outcomes.

As the use of multiple AI agents becomes more common, there's the additional complexity of coordination between agents. Without proper orchestration, agents may take

contradictory actions or duplicate efforts. Ensuring seamless collaboration among specialized agents—for tasks like onboarding, compliance, and credit scoring—requires new frameworks for communication, delegation, and shared context.

Lastly, cultural and workforce resistance remains a human barrier to adoption. Employees may fear job displacement or struggle to adapt to new workflows driven by autonomous systems. This highlights the importance of change management, transparent communication, and upskilling programs that position AI as a tool for empowerment rather than replacement.

Future Direction

The future of multimodal agentic AI in banking and finance is poised to redefine the way financial institutions operate, interact with customers, and deliver value. Rather than aiming for full automation and workforce replacement, the direction is shifting toward human-AI collaboration, where AI agents function as co-pilots that enhance human decision-making. These agents will increasingly serve as the primary interface between customers and banks, enabling seamless interactions across voice, text, documents, images, and even gestures. This evolution will move customer experiences away from static apps and web forms to dynamic, conversational, and context-aware interfaces that operate across devices and platforms.

In the coming years, AI agents will become goal-driven financial assistants capable of understanding long-term financial objectives and acting proactively to help users plan, save, invest, and borrow. These agents will not only understand multimodal inputs — such as a spoken financial goal or a scanned income document — but will also personalize actions based on behavioral, contextual, and historical data. Additionally, as the financial ecosystem becomes more open and interoperable, we will see the rise of personal finance agents that operate across multiple institutions on behalf of the user, negotiating with banks, insurers, and wealth platforms in a secure and decentralized manner.

To support such autonomy, banks will need to adopt architectures that ensure transparency, explainability, and accountability. Regulations will demand auditability of AI decisions, and financial institutions will embed governance frameworks into their AI systems to track and justify every decision made by an agent. These systems will include agent-level logs, real-time compliance checks, and ethical guardrails to prevent bias, discrimination, and unintended actions. Security and privacy will also be paramount, with multimodal AI agents needing to guard against deepfakes, identity spoofing, and data leakage across sensitive voice and image inputs.

Simultaneously, AI agents will become more intelligent and self-improving. Through federated learning and real-time feedback loops, agents will continuously adapt to new regulations, products, and customer behaviors without requiring constant reprogramming. Banks will begin adopting modular agent frameworks, where different AI agents — for identity verification, fraud detection, compliance, lending, and advisory — work together, sharing context through orchestration platforms like LangGraph or AutoGen.

Importantly, these advances will enable greater financial inclusion. Voice-first and camera-enabled AI agents will support users with low literacy, limited access to formal banking, or basic mobile phones. By operating in local languages, offline modes, and through intuitive interfaces, banks can reach millions in underserved communities, offering credit, savings, and insurance services where branches can't go.

Finally, the strategic focus will shift from merely deploying AI to governing it effectively. Ethical and transparent AI will become a core element of brand trust and competitive advantage. Banks that invest in responsible AI — ensuring fairness, reliability, and compliance by design — will be better positioned to gain customer loyalty and regulatory confidence in the years ahead.

CONCLUSION

In conclusion, the emergence of multimodal agentic AI marks a transformative shift in the banking and finance sector, with the potential to redefine how financial services are delivered, managed, and experienced. These intelligent systems are moving beyond narrow automation to take on adaptive, goal-oriented roles that were once the exclusive domain of skilled human professionals. From streamlining customer interactions and enhancing fraud detection to automating compliance and democratizing financial access, AI agents are reshaping operational efficiency and customer engagement at scale.

However, as this transformation unfolds, it is accompanied by complex challenges—ranging from data privacy and algorithmic bias to explainability and regulatory compliance—that demand strategic attention and robust

governance. The path forward requires a thoughtful balance: leveraging the power of AI agents to drive innovation and inclusion, while embedding strong ethical, legal, and operational safeguards to ensure transparency, fairness, and accountability.

Ultimately, the future of finance will not be defined solely by automation, but by human-AI collaboration, where intelligent agents work alongside people to create smarter, safer, and more inclusive financial systems. Institutions that proactively embrace this evolution—while staying committed to responsible innovation—will not only gain a competitive edge but also shape a more resilient and accessible financial future for all.

ACKNOWLEDGEMENT

We would like to express our sincere thanks to Dr. G. T. Thampi (Principal, Thadomal Shahani Engineering College, Mumbai) and Dr. Madhuri Y. Rao (Head, AI/DS Department, Thadomal Shahani Engineering College, Mumbai) for their guidance and mentorship.

REFERENCES

1. The future of India's BFSI sector: How Agentic AI is powering autonomous operations - https://cio.economictimes.indiatimes.com/news/artificial-intelligence/how-agentic-ai-is-rewiring-bfsi-workflows/121498617#:~:text=Agentic%20AI%20is%20revolutionizing%20the,analysis%20and%20proactive%20security%20measures
2. How Agentic AI will transform financial services | World Economic Forum - https://www.weforum.org/stories/2024/12/agentic-ai-financial-services-autonomy-efficiency-and-inclusion/
3. Agentic AI will be the real banking disruptor - The Banker - https://www.thebanker.com/content/886b880f-fc01-458d-81a5-4ad4c27815da
4. The AI-Led Banker: How Agentic AI is Reinventing Banking from the Inside Out - https://wiprotechblogs.medium.com/agentic-ai-solutions-revolutionizing-bfsi-operations-d3df8d38f1d7
5. Agentic AI and the future of fintech and banking automation - FinTech Futures - https://www.fintechfutures.com/ai-in-fintech/agentic-ai-and-the-future-of-fintech-and-banking-automation
6. A Multimodal Foundation Agent for Financial Trading: Tool-Augmented, Diversified, and Generalist - https://arxiv.org/abs/2402.18485?utm_source=chatgpt.com
7. FinRobot: An Open-Source AI Agent Platform for Financial Applications using Large Language Models - https://arxiv.org/abs/2405.14767
8. FinTral: A Family of GPT-4 Level Multimodal Financial Large Language Models - https://arxiv.org/abs/2402.10986
9. Revolutionizing Banking Operations with AI Agents- https://www.akira.ai/blog/banking-operations-with-ai-agents
10. How agentic AI will revolutionize the financial services landscape - https://www.cognizant.com/us/en/insights/insights-blog/agentic-ai-systems-revolutionizing-financial-services
11. Agentic AI Finance & the 'Do It For Me' Economy - https://www.citigroup.com/global/insights/agentic-ai
12. 9 essential benefits of agentic AI in financial services - https://www.symphonyai.com/resources/blog/financial-services/benefits-agentic-ai/
13. Agentic AI In Banking: The Future And The Challenges - https://www.forbes.com/councils/forbestechcouncil/2025/05/05/agentic-ai-in-banking-the-future-and-the-challenges/
14. Agentic AI in Financial Services: The Future of Intelligent Automation - https://www.endava.com/insights/articles/agentic-ai-in-financial-services-the-future-of-intelligent-automation

Ways and Means of Indian Banks Evolving as Fintech Enterprises leveraging Multimodal Agentic AI

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ABSTRACT

The Indian banking sector is going through intense digital transformation. This change is driven by swift advancements in AI and rising demand of customers for quick, seamless and intelligent financial services. This shift is being led by agentic AI—a new generation of AI systems capable of autonomous decision-making, multimodal interaction, and continuous learning. This paper explores the strategic pathways through which Indian banks can evolve into fintech-driven enterprises by leveraging agentic AI. It outlines key roles that AI agents can assume across banking functions such as customer engagement, credit underwriting, fraud detection, compliance, and personalized financial advisory. The study contrasts traditional human-driven processes with emerging AI-powered approaches, highlighting areas where automation and augmentation can create operational efficiencies, enhance customer experience, and drive financial inclusion. It also discusses the potential impact of these technologies, the regulatory and ethical challenges they pose, and the infrastructural changes required for integration. Finally, the paper presents a forward-looking roadmap for Indian banks to adopt agentic AI responsibly focusing on innovation, collaboration with fintech ecosystems, and governance frameworks that ensure transparency, accountability, and trust. As India positions itself as a global digital leader, the convergence of banking and agentic AI presents a transformative opportunity to redefine the future of financial services.

KEYWORDS *: Agentic AI, Automation, Banking, Fintech enterprise.*

INTRODUCTION

Much like their global counterparts, Indian banks, today, are at a crucial juncture where they must upgrade their legacy systems to modern technologies as also innovate to remain competitive in a dynamically evolving and rapidly expanding fintech ecosystem. Agentic AI promises to deliver this transformation. It blends the ability to process various types of data—like text, images, voice, and other inputs—with the capacity to make independent decisions and act intelligently. Conventional AI typically responds reactively to specific tasks, while Agentic AI works as a proactive system that can reason, plan, decide, act, learn and improve continuously. With multimodal capabilities, these AI agents can interact seamlessly with both customers and internal systems across different input and output formats thus enabling banks to deliver highly personalized and efficient financial services and driving their transformation into agile, intelligent, and customer-centric fintech or fintech-style enterprises.

This paper inspects the ways on how Multimodal Agentic AI can be leveraged by Indian banks to transform key

business areas like customer onboarding, customer management, fraud detection, credit assessment, lending process, regulatory adherence, wealth management, and personalized financial advisory etc. It examines how manual and labor-intensive processes can be automated using AI. It also delves into some important factors that will influence this transformation—like regulatory and ethical considerations, infrastructure requirements and workforce (re)skilling. This study aims to contribute to the broader conversation on the future of banking in India by advising a pathway for responsible adoption of AI and enabling banks to evolve into platform-driven Fintech leaders.

MULTIMODAL AGENTIC AI IN DIGITAL ERA

As we step deeper into the digital era, artificial intelligence is evolving from narrow, task-specific tools to intelligent, autonomous systems capable of reasoning, planning, and interacting across multiple modes of input. This evolution has given rise to multimodal agentic AI—a new class of AI systems that not only comprehend and generate responses across text, image, audio, and video inputs but also act with goal-oriented autonomy. These agents can make decisions, adapt to dynamic environments, and execute tasks with minimal human intervention. Their emergence marks a significant inflection point in the design of human-machine interaction, offering transformative applications across industries including healthcare, education, governance, and financial services.

Multimodal agentic AI combines two critical advances in artificial intelligence: multimodal learning and agentic behavior. Multimodal learning refers to the ability of AI systems to process and correlate information from different formats—text, speech, vision, and sensor data—to build a more comprehensive understanding of tasks or contexts. Agentic behavior, on the other hand, describes AI systems that can proactively set goals, plan sequences of actions, make decisions, and revise their strategies in response to feedback or environmental change. Together, these capabilities allow machines to function not merely as tools, but as intelligent collaborators capable of interacting in real-world, complex, and ambiguous environments.

Applications Across Sectors

In the digital era, multimodal agentic AI is poised to redefine automation, decision-making, and customer experience. In healthcare, such agents can interpret radiology images, medical histories, and patient speech in real time to assist in diagnosis and care coordination. In education, they can serve as adaptive tutors—interpreting student queries through voice and writing, and tailoring content dynamically across visual and verbal media. In customer service and finance, multimodal agents act as smart assistants capable of understanding user intent through voice commands, facial expressions, uploaded documents, and behavioral patterns—delivering personalized responses and executing transactions with minimal supervision.

The integration of agentic AI is also central to the rise of digital twins, autonomous vehicles, and smart cities—where real-time, multimodal perception and decision-making are essential for safety, efficiency, and personalization. Furthermore, these agents can operate in low-resource environments, enabling inclusive digital access for populations with limited literacy or technological fluency, using voice, images, and gestures instead of only text-based interfaces.

Challenges and Ethical Considerations

Despite their immense potential, multimodal agentic AI systems face substantial challenges. The complexity of fusing multiple data types introduces issues in model alignment, training data imbalance, and semantic coherence. Bias, explainability, and fairness become even more critical in such systems, as errors in one modality can compound across others—leading to misinterpretations or unjust outcomes. Moreover, the agentic nature of these systems introduces new questions around autonomy, accountability, and safety, particularly in high-stakes domains like finance, healthcare, and law.

There are also concerns about privacy and surveillance, as multimodal systems often require continuous access to cameras, microphones, and sensitive personal data. Regulatory frameworks have yet to fully catch up with these advancements, and there is a growing need for standards that guide responsible design, deployment, and governance of agentic AI.

Future Directions on Agentic AI Era

The future of multimodal agentic AI lies in human-centered design, where agents work alongside individuals, augmenting human capabilities rather than replacing them. Research must prioritize explainable, trustworthy, and privacy-preserving architectures, along with tools for model introspection and ethical evaluation. Cross-disciplinary collaboration will be crucial—bringing together technologists, ethicists, domain experts, and policymakers to shape the trajectory of these powerful systems.

Advancements in compute infrastructure, foundation models, and real-time edge processing will further enable the deployment of multimodal agents in decentralized and resource-constrained environments. As society becomes increasingly reliant on digital systems, multimodal agentic AI offers a pathway to richer, more adaptive, and inclusive machine intelligence—if developed and governed responsibly.

MULTIMODAL AI AGENTS IN FINTECH ENTERPRISES

Multimodal agentic AI offers fintech enterprises a powerful lever to accelerate innovation, scale operations, and deliver hyper-personalized financial experiences. Unlike traditional automation tools, agentic AI systems are not limited to executing predefined rules—they can understand goals, plan actions, reason through uncertainty, and make autonomous decisions across dynamic contexts. When enhanced with multimodal capabilities, these agents can process and respond to a wide array of inputs—such as customer voice queries, handwritten forms, scanned documents, and behavioral data—making them highly versatile in real-world financial interactions. This flexibility enables fintechs to provide seamless, omnichannel experiences that mimic human understanding while operating at machine speed and scale.

For customer engagement, these agents can serve as always-on virtual relationship managers, offering real-time support, financial advice, and transaction handling through conversational interfaces. In backend operations, they automate complex workflows such as KYC verification, fraud monitoring, loan origination, and compliance reporting by intelligently extracting and synthesizing data from multiple formats. This reduces turnaround times, cuts operational costs, and minimizes human error—giving fintechs a clear efficiency edge. Additionally, agentic AI facilitates continuous learning from user interactions and outcomes, enabling systems to adapt to new regulations, market conditions, and customer behaviors without requiring constant reprogramming.

Most importantly, multimodal agentic AI enhances financial inclusivity by enabling services that are accessible to users across languages, literacy levels, and geographies. For instance, a user in a rural area with low literacy could apply for a loan through voice input and ID photo submission—tasks the agent can process instantly. Overall, by embedding intelligence, adaptability, and accessibility into their core offerings, fintech enterprises leveraging multimodal agentic AI can deliver next-generation financial services that are faster, smarter, and more inclusive.

EVOLVING INDIAN BANKS INTO FINTECH ENTERPRISES THROUGH MULTIMODAL AGENTIC AI

The convergence of banking and fintech is accelerating in India, driven by digital adoption, regulatory support, and evolving customer expectations. To remain competitive and relevant, Indian banks must transition from legacy, transaction-oriented institutions to intelligent, agile, and service-driven fintech enterprises. A key enabler of this evolution is multimodal agentic AI, which allows machines to not only process diverse inputs like text, voice, images, and documents, but also act autonomously, learn continuously, and make context-aware decisions. This shift redefines traditional banking roles across multiple domains.

Customer Onboarding and KYC

Traditionally, customer onboarding in Indian banks has involved significant paperwork, manual verification, and time-consuming checks. Multimodal agentic AI can streamline this by integrating facial recognition, document OCR (Optical Character Recognition), speech recognition, and biometric verification. An AI agent can autonomously extract and cross-verify information from ID documents, compare facial images with live video or selfies, understand verbal

instructions, and validate against regulatory databases like Aadhaar, PAN, or CKYC. This reduces onboarding time from days to minutes and enhances compliance without human intervention.

Customer Support and Relationship Management

Multilingual, multimodal AI agents can engage with customers through voice, chat, and visual inputs, enabling personalized support across mobile apps, web portals, and call centers. These agents can interpret queries, retrieve relevant account or transaction information, escalate complex issues, and even offer proactive financial advice. In a multilingual market like India, where language diversity is vast, such agents ensure inclusivity and improved customer satisfaction. They can also act as virtual relationship managers for mass-affluent and retail clients, once only served by branch-based staff.

Credit Risk Assessment and Loan Processing

Agentic AI systems can assess creditworthiness by analyzing a combination of structured financial data and unstructured data such as employment verification letters, utility bills, or even behavioral patterns derived from mobile usage. Unlike traditional scorecard models, AI agents can dynamically adjust risk profiles and provide near-instant loan approvals, especially for underserved populations such as gig workers or rural customers. This expands credit access while improving risk management.

Fraud Detection and Security

By analyzing multimodal data—such as voice tone, facial cues during authentication, transaction patterns, and device metadata—AI agents can detect anomalies and flag potential fraud in real time. They can act autonomously to block transactions, trigger alerts, or request additional verification, thereby reducing the need for manual fraud investigation teams. These systems also adapt to evolving fraud techniques by learning from new patterns and contexts.

Wealth Management and Investment Advisory

Multimodal AI agents can act as robo-advisors, interpreting user input through speech, documents, or forms to understand financial goals, risk tolerance, and investment history. They can generate personalized portfolio recommendations, simulate outcomes, and provide interactive reports with voice and visual explanations. This democratizes wealth advisory services, making them accessible to a broader population at lower cost and with higher scalability.

Regulatory Compliance and Reporting

Agentic AI can automate the monitoring of transactions, emails, customer interactions, and internal communications to ensure compliance with RBI and SEBI norms. These agents can autonomously flag suspicious activities, prepare audit trails, and generate real-time reports for regulators. Multimodal processing enables them to understand not only numerical data but also legal documents, customer forms, and transcripts—improving the scope and accuracy of compliance systems.

Internal Operations and Workforce Augmentation

Beyond customer-facing functions, banks can deploy agentic AI to optimize internal workflows. Agents can manage repetitive tasks like document classification, email triage, employee onboarding, and knowledge base management. They can serve as intelligent assistants to bank staff—retrieving documents, summarizing regulations, or suggesting next steps—freeing employees to focus on higher-order decision-making and relationship building.

CHALLENGES IN ADOPTING MULTIMODAL AGENTIC AI IN INDIAN BANKING

While the adoption of multimodal agentic AI offers transformative potential for Indian banks, its integration is not without significant challenges—technical, regulatory, operational, and cultural. One of the foremost obstacles is data quality and infrastructure readiness. Legacy core banking systems often operate in silos, with fragmented and inconsistent data that hampers AI model performance. The multimodal nature of agentic AI requires clean, integrated datasets across text, voice, image, and structured data sources—something many Indian banks are still far from achieving.

Additionally, regulatory compliance and explainability pose major hurdles. The Reserve Bank of India (RBI) and other financial regulators demand transparency

and accountability in all decision-making processes, especially in areas like lending, fraud detection, and customer service. However, agentic AI systems—especially those using deep learning and autonomous reasoning—often function as "black boxes," making it difficult to trace how decisions were made. Without robust explainability and audit mechanisms, deployment in critical functions remains risky and potentially non-compliant.

Bias and fairness are also critical concerns. If AI agents are trained on biased or incomplete data—especially in a socio-economically diverse country like India—they may unintentionally discriminate against certain customer segments, exacerbating financial exclusion. Multimodal systems introduce even more complexity, as bias may arise from voice, facial data, or document formats, leading to fairness issues across multiple modalities.

Cybersecurity and privacy are further concerns, as multimodal systems collect and process sensitive personal data across various channels. Ensuring data protection under frameworks like the Digital Personal Data Protection Act (DPDPA) while enabling real-time, AI-driven interactions is a difficult balance. Moreover, the cost and skill gap associated with deploying and maintaining such sophisticated AI infrastructure remains steep. Most Indian banks, particularly public sector ones, face talent shortages in AI, data science, and MLOps (machine learning operations), and may rely heavily on third-party fintech partnerships, introducing dependencies and risks.

Lastly, organizational inertia and change management cannot be overlooked. Embedding agentic AI into workflows challenges long-standing hierarchies, roles, and processes. Resistance to change, lack of digital culture, and concerns about job displacement may hinder adoption across departments. Therefore, Indian banks must take a holistic approach—combining technology, governance, upskilling, and stakeholder trust—to overcome these challenges and fully unlock the potential of multimodal agentic AI.

FUTURE DIRECTION

Looking ahead, the evolution of Indian banks into fintech-like enterprises through multimodal agentic AI will depend on strategic, phased advancement across technology, policy, and organizational dimensions. A key future direction lies in developing hybrid human-AI collaboration models, where AI agents handle high-volume, multimodal data tasks autonomously, while humans provide oversight in complex, ethical, or regulatory-sensitive scenarios. This approach can enhance trust, accountability, and operational resilience. Banks must also prioritize AI explainability and governance frameworks, integrating tools for model transparency, bias detection, and auditability to meet the growing demands of regulators and consumers alike. Another critical area is AI infrastructure modernization—including scalable cloud platforms, secure data lakes, and unified APIs—which will enable seamless orchestration of multimodal inputs across functions.

Furthermore, inclusive AI design will be vital to ensuring that these innovations serve India's vast and diverse population. This includes training AI systems in multiple regional languages, adapting to varied literacy levels, and ensuring accessibility through voice-first and visual interfaces. Partnerships with fintech startups, regtech firms, and academic institutions will continue to play a crucial role in bridging talent gaps, accelerating innovation, and co-developing domain-specific solutions. From a policy perspective, alignment with frameworks such as the Reserve Bank of India's Digital Banking Unit (DBU) initiative and the Digital Personal Data Protection Act (DPDPA) will be essential to ensure secure and ethical deployment.

Ultimately, the future of Indian banking in the AI era will hinge on creating agile, intelligent, and responsible ecosystems, where multimodal agentic AI acts not just as a support system, but as a catalyst for reimagining the very architecture of financial services—making them more efficient, inclusive, and responsive to the dynamic needs of a digital-first economy.

CONCLUSION

The transformation of Indian banks into fintech-style enterprises is no longer a distant vision but an emerging reality, powered by the growing capabilities of multimodal agentic AI. By enabling intelligent, goal-driven, and multimodal interactions, these AI agents offer a significant leap beyond traditional automation—facilitating real-time decision-making, personalized

customer experiences, and operational efficiency across the financial value chain. From customer onboarding and credit assessment to compliance and advisory services, multimodal agentic AI promises to reshape banking into a more agile, inclusive, and data-driven enterprise.

However, realizing this potential requires more than technological investment. Indian banks must navigate a complex landscape of regulatory compliance, ethical responsibility, infrastructure modernization, and cultural transformation. Addressing challenges related to data quality, explainability, fairness, and cybersecurity will be essential for sustainable adoption. At the same time, fostering partnerships with Fintech, regulators, and research institutions can accelerate innovation while ensuring alignment with national priorities and customer trust.

In conclusion, the integration of multimodal agentic AI represents both a strategic imperative and a transformative opportunity for Indian banks. Those that embrace this shift thoughtfully—balancing innovation with responsibility—will not only redefine their competitive edge but also contribute meaningfully to the broader goal of financial inclusion, digital resilience, and economic empowerment in India's rapidly evolving financial ecosystem.

ACKNOWLEDGEMENT

We would like to express our sincere thanks to Dr. G. T. Thampi (Principal, Thadomal Shahani Engineering College, Mumbai) and Dr. Madhuri Y. Rao (Head, AI/DS Department, Thadomal Shahani Engineering College, Mumbai) for their guidance and mentorship.

REFERENCES

1. Digital Transformation in Indian Banking: Navigating Disruption and Opportunity - https://www.linkedin.com/pulse/digital-transformation-indian-banking-navigating-surya-prakash-qw1bf
2. Evolving "Indian Banking" Landscape: Trends, Opportunity & Challenges - https://www.bankingfinance.in/evolving-indian-banking-landscape-trends-opportunity-challenges.html?utm_source=chatgpt.com
3. From data to decisions: how AI is revolutionizing fintech operations in 2025 - https://cio.economictimes.indiatimes.com/news/artificial-intelligence/from-data-to-decisions-how-ai-is-revolutionizing-fintech-operations-in-2025/117318997
4. Agentic AI comes with Agentic UX: Indian PSBs must move before the world moves on - https://medium.com/digital-banking-2030/agentic-ai-comes-with-agentic-ux-indian-psbs-must-move-before-the-world-moves-on-83be64ebb184
5. AI Applications in the Top 4 Indian Banks - https://emerj.com/ai-applications-in-the-top-4-indian-banks/
6. Building future-ready workforce in banking sector leveraging Digital Public Infrastructure (DPI) - https://www.ey.com/en_in/insights/banking-capital-markets/building-future-ready-workforce-in-banking-sector-leveraging-dpi
7. 4 ways AI is streamlining banking in India - https://www.weforum.org/stories/2023/12/how-ai-can-streamline-indian-banking/
8. How AI is Powering the Next Wave of FinTech in India - https://indiatechnologynews.in/how-ai-is-powering-the-next-wave-of-fintech-in-india/#:~:text=AI%20is%20at%20the%20core,cyber%20fraud%20in%20real%2Dtime
9. Indian Startups With Unique Fintech Solutions That Use AI Algorithms And Models - https://inc42.com/features/10-indian-startups-with-unique-fintech-solutions-that-use-ai-algorithms-and-models/?utm_source=chatgpt.com
10. GenAI Can Help Fintech Sector Comply With Evolving Regulations, Say Experts - https://inc42.com/buzz/genai-can-help-fintech-sector-comply-with-evolving-regulations-say-experts/?utm_source=chatgpt.com
11. How can Agentic AI strengthen India's banking ecosystem and reach the last-mile customers? - https://bfsi.eletsonline.com/how-can-agentic-ai-strengthen-indias-banking-ecosystem-and-reach-the-last-mile-customers/
12. AI in Banking: Applications, Benefits, and Use Cases - https://aisera.com/blog/generative-ai-in-banking/
13. The changing face of financial services: Growth of FinTech in India - https://www.pwc.in/assets/pdfs/consulting/financial-services/fintech/publications/the-changing-face-of-financial-services-growth-of-fintech-in-india-v2.pdf
14. Transforming Agentic Process Automation with Finance and Banking - https://www.xenonstack.com/blog/agentic-process-automation-finance-banking
15. Smart Money: How AI is Disrupting India's BFSI Game - https://analyticsindiamag.com/ai-features/smart-money-how-ai-is-disrupting-indias-bfsi-game/

A Survey on Hierarchical and BiLSTM-Based Architectures for Named Entity Recognition

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ABSTRACT

Named Entity Recognition (NER) is a fundamental task in Natural Language Processing (NLP), essential for information extraction, question answering, and knowledge organization. Among neural sequence labeling models, Bidirectional Long Short-Term Memory (BiLSTM) networks have become a widely used backbone due to their ability to model contextual dependencies in text. More recent developments have introduced hierarchical extensions that incorporate multi-level context spanning words, sentences, and documents to better address challenges such as entity ambiguity, out of vocabulary recognition, and long-range dependencies. This survey provides a comprehensive overview of BiLSTM-based and hierarchical NER architectures. It reviews advancements in encoding strategies, integration of contextual cues at various granularity levels, and decoding techniques including CRF and Softmax classifiers. Key benchmark datasets such as CoNLL-2003 and OntoNotes 5.0 are discussed along with evaluation metrics that assess generalization across diverse entity types and linguistic conditions. The survey also outlines ongoing challenges and future directions, with a focus on lightweight modeling, domain adaptation, and scalable hierarchical designs for NER.

KEYWORDS *: Named entity recognition (NER), BiLSTM, Hierarchical NER, Sequence labeling, Contextual representation, Neural architectures, CRF decoder, Softmax classifier, Out-of-vocabulary (OOV) Entities, Span-based NER, Low-resource NLP, Multilingual NER, Nested entities, Document-level NER, Evaluation metrics.*

INTRODUCTION

Named Entity Recognition (NER) is a foundational task in Natural Language Processing (NLP), aimed at identifying and classifying entities such as persons, organizations, locations, and temporal expressions within unstructured text. As a core component of information extraction pipelines, NER plays a critical role in a wide range of applications, including question answering, knowledge base population, and event detection [1], [17].

Early NER systems relied heavily on handcrafted rules, lexicons, and statistical models such as Hidden Markov Models (HMMs) and Conditional Random Fields (CRFs) [2], [3]. These methods, while effective in structured domains, struggled to generalize across diverse contexts due to their limited capacity to capture semantic and syntactic variability.

With the advent of deep learning, neural network-based models began to outperform traditional techniques by learning contextual representations directly from data. Among these, Bidirectional Long Short-Term Memory (BiLSTM) networks emerged as a particularly effective architecture for sequence labeling tasks [4], [5]. The BiLSTM's ability to process input in both forward and backward directions enables it to model dependencies beyond local windows, a critical advantage in recognizing entities within complex sentence structures.

To further enhance sequence labeling performance, researchers have commonly integrated BiLSTM encoders with CRF decoders [4], [6], [7]. Such combinations allow the model to capture both token-level features and label dependencies, leading to improved consistency in predicted sequences. Additionally, several works have enriched input representations by incorporating character-level embeddings or convolutional neural features [6], [7], resulting in robust handling of rare or morphologically rich words.

More recently, attention has shifted toward hierarchical NER models that incorporate multiple levels of contextual abstraction—word, sentence, and document—within the network. These models aim to overcome limitations in flat sequence encoders by integrating broader contextual cues, which are particularly useful for entity disambiguation, out-of-vocabulary recognition, and modeling long-range dependencies [8]–[12]. Hierarchical BiLSTM

architectures, in particular, maintain the core advantages of recurrent networks while introducing sentence-level or document-level encoders to capture global structure.

This survey provides a comprehensive overview of BiLSTM-based and hierarchical approaches for NER. We examine the evolution of neural architectures, the various ways in which hierarchical context is modeled, and decoder strategies including CRF, Softmax, and span-based labeling. Benchmark datasets such as CoNLL-2003 and OntoNotes 5.0 [1], [17], along with evaluation settings for in-vocabulary (IV), out-of-training-vocabulary (OOTV), out-of-embedding-vocabulary (OOEV), and out-of-both-vocabularies (OOBV), are discussed in depth [18], [19].

We aim to equip researchers with a clear understanding of the strengths, limitations, and ongoing challenges in designing NER models that leverage contextual information efficiently. Through this survey, we highlight architectural innovations, empirical trends, and future research opportunities in the domain of structured, context-aware named entity recognition.

EVOLUTION OF NAMED ENTITY RECOGNITION TECHNIQUES

The development of Named Entity Recognition (NER) techniques has progressed through three main stages: rule-based/statistical approaches, neural network-based models, and context-aware hierarchical architectures. Each stage addressed limitations of its predecessor, leading to the current generation of high-performing NER systems.

Rule-Based and Statistical Methods

Initial NER systems were constructed using handcrafted rules, gazetteers, and pattern-matching techniques. These were effective in controlled domains but failed to generalize well.

With the availability of annotated corpora, statistical models became prevalent. Hidden Markov Models (HMMs) and Maximum Entropy Markov Models (MEMMs) laid the foundation for probabilistic sequence labeling. These were soon outperformed by Conditional Random Fields (CRFs), which allowed global sequence optimization using rich, overlapping features [3].

Table 1. Comparison of Early Statistical NER Models

Model	Strengths	Limitations	Reference
HMM	Simple, probabilistic	Assumes Markov property, limited features	[2]
MEMM	Allows rich features	Suffers from label bias	[2]
CRF	Global sequence modeling, feature flexibility	Requires manual feature engineering	[3]

The CoNLL-2003 Shared Task standardized evaluation practices and accelerated research in statistical NER [1].

Neural Network-Based Models

The rise of deep learning led to a shift from feature-engineered models to representation learning. Early efforts used feedforward neural networks and convolutional neural networks (CNNs), but lacked sequential modeling capabilities.

The introduction of Long Short-Term Memory (LSTM) networks solved the vanishing gradient problem and allowed for modeling long-distance dependencies. Bidirectional LSTMs (BiLSTMs) further enhanced context capture by processing sequences in both directions [4], [5].

To enforce label consistency and model transition dependencies, BiLSTM outputs were paired with CRF layers. The resulting BiLSTM-CRF architecture became a de facto standard [4], [6].

Table 2. Advancements in Neural NER Models

Model	Key Components	Strengths	Reference
BiLSTM	Word-level BiLSTM	Context-aware token encoding	[5]
BiLSTM-CRF	BiLSTM + CRF	Consistent label sequences	[4], [6]
BiLSTM-CNN-CRF	Adds char-level CNN embeddings	Handles rare/ morphologically rich tokens	[6], [7]

These architectures demonstrated strong performance on datasets like CoNLL-2003 and OntoNotes 5.0, with minimal feature engineering.

Toward Context-Aware and Hierarchical Modeling

Despite their success, flat BiLSTM models struggled with long-range dependencies and lacked document-level context. To address this, researchers proposed hierarchical architectures that incorporate multiple levels of granularity—word, sentence, and document [8] [12].

Hierarchical models typically involve:

- A word-level BiLSTM for local context
- A sentence-level BiLSTM for global structure

- Pooling mechanisms (mean, max) to derive sentence vectors

Table 3.Characteristics of Hierarchical NER Models

Model	Architecture Levels	Benefits	Reference
Hierarchical BiLSTM [9]	Word + Sentence	Captures inter-sentence dependencies	[9], [11]
Multi-Level Typing [8]	Word + Doc Context	Improves fine-grained classification	[8]
Nested NER Models [10]	Layered span encoding	Supports nested entities	[10], [12]

Such architectures improve recognition of complex entities, support nested structures, and enhance out-of-vocabulary generalization.

BILSTM-BASED ARCHITECTURES FOR NAMED ENTITY RECOGNITION

Bidirectional Long Short-Term Memory (BiLSTM) networks have emerged as a central architecture in modern Named Entity Recognition (NER) due to their effectiveness in modeling sequential dependencies. By processing input sequences in both forward and backward directions, BiLSTMs generate context-rich representations for each token, which are essential for accurate entity classification. This section presents a taxonomy of BiLSTM-based architectures, enhancements in input representations, decoding strategies, and key model variants.

Core BiLSTM-CRF Architecture

The BiLSTM-CRF model, first popularized by Huang et al. [4], combines BiLSTM's contextual encoding with a Conditional Random Field (CRF) decoder that enforces valid label transitions. This architecture quickly became the standard for sequence labeling tasks, including NER.

- BiLSTM Layer: Generates token-level hidden states using both past and future context.
- CRF Layer: Predicts the optimal sequence of entity labels, considering inter-label dependencies.

Table 4.Advantages of the BiLSTM-CRF Architecture

Component	Role	Benefit	Reference
BiLSTM Encoder	Captures bidirectional context	Context-aware token representation	[5]
CRF Decoder	Applies structured prediction over labels	Ensures globally coherent output	[4], [6]

Enhancements in Input Representations

To improve the quality of input embeddings, various works have integrated character-level, subword, and pretrained word embeddings into BiLSTM-based NER systems.

- Character-Level CNN or BiLSTM: Models subword features such as prefixes, suffixes, and inflectional patterns [6], [7].
- Pretrained Embeddings: GloVe, Word2Vec, or FastText vectors are commonly used for initialization [5].
- Hybrid Embeddings: Concatenating word-level and character-level embeddings enhances robustness, especially for rare or unseen words.

Table 5. Common Embedding Strategies in BiLSTM-Based NER

Embedding Type	Description	Contribution to NER Accuracy	Reference
GloVe / Word2Vec	Static word embeddings	General semantic context	[5]
Char-CNN	Convolution over characters	Morphological robustness	[6]
Char-BiLSTM	Sequence modeling over characters	Context-aware subword info	[7]
Hybrid Embeddings	Word + Char (CNN/ BiLSTM)	Best for OOV and rare words	[6], [7]

Decoder Variants: CRF vs. Softmax

Two primary decoding strategies are used in BiLSTM-based NER models:

CRF Decoder

- Computes optimal label sequence using transition scores.
- Well-suited for BIO and BILOU schemes.
- Performs best when label dependencies are important.

Softmax Decoder

- Independently predicts label for each token.
- Faster, but may produce inconsistent sequences.

Table 6. Comparison of Decoding Strategies

Deco-der	Mechanism	Pros	Cons	Reference
CRF	Sequence-level decoding	Global label consistency	Slower inference	[4], [6]

Softmax	Token-level classification	Fast, simple	May produce invalid label sequences	[5]

D. Notable Variants of BiLSTM-Based Models

Many research efforts have adapted the base BiLSTM-CRF structure to improve robustness, performance, or applicability to specific scenarios:

- BiLSTM-CNNs-CRF: Uses CNNs for character-level embeddings [6].
- BiLSTM + Char BiLSTM + CRF: Combines BiLSTM at both character and word levels [7].
- BiLSTM + ELMo/BERT Embeddings: Injects pretrained contextual embeddings (early use before full transformers) [13].

Table 7. Variants of BiLSTM-Based Models

Model Name	Enhancements	Strengths	Reference
BiLSTM-CRF	Base model	Strong baseline, sequence coherence	[4]
BiLSTM-CNNs-CRF	Character CNN	Handles subword variation	[6]
BiLSTM + Char BiLSTM-CRF	Dual-level BiLSTM	Enhanced subword sequence modeling	[7]
BiLSTM + Contextual Embeds	Uses ELMo/ BERT (without full transformer)	Better semantic understanding	[13]

Evaluation on Benchmarks

BiLSTM-based models have achieved high performance on standard NER benchmarks like CoNLL-2003 and OntoNotes 5.0. Evaluation metrics include Precision, Recall, F1-Score, and more nuanced metrics for OOV analysis such as IV, OOTV, OOEV, and OOBV [18], [19].

These models have demonstrated:

- Strong generalization across domains
- High F1 scores on both English and multilingual datasets
- Limitations in long-sequence modeling and cross-sentence context (addressed later via hierarchical modeling)

HIERARCHICAL NAMED ENTITY RECOGNITION MODELS

Although BiLSTM-based architectures have significantly advanced the performance of Named Entity Recognition (NER), their effectiveness is often constrained by the limited scope of context they can model. Standard BiLSTM models typically operate at the sentence level, encoding local token-level dependencies but failing to fully exploit inter-sentence or document-level semantic information. This limitation becomes especially problematic in real-world scenarios involving long documents, context-dependent entity mentions, or disambiguation across sentence boundaries. To address these challenges, researchers have proposed hierarchical NER models, which aim to incorporate multiple levels of contextual information—spanning words, sentences, and documents—within a unified architecture [8] [12].

Hierarchical NER models are motivated by the need to represent text at different granularities. While word-level encoders such as BiLSTMs provide effective representations for local dependencies, they cannot capture relationships across multiple sentences or recognize discourse-level cues. Hierarchical models address this by introducing a second level of encoding: after processing each sentence through a word-level BiLSTM, sentence embeddings are computed—often using mean or max pooling over token-level outputs—and passed through a sentence-level BiLSTM. This layered approach allows the model to capture dependencies not only within but also across sentences, improving its ability to disambiguate entity mentions and maintain coherence across longer texts [9], [11].

A range of architectural strategies has been explored within this framework. For instance, Lin et al. [8] proposed a multi-level contextualized representation model for fine-grained entity typing, integrating sentence and document-level context. Similarly, Zhang and Wang [9] introduced a hierarchical attention-based NER model for long documents, showing that sentence-level encoding significantly improves performance on lengthy inputs. Ju et al. [10] focused on nested named entity recognition by designing a layered neural model that handles overlapping spans through recursive encoding. Luo et al. [11] extended these ideas further with hierarchical contextualized representations that leverage sentence-level BiLSTMs to model entity interactions across discourse segments.

Sentence representations in hierarchical models are typically obtained through pooling mechanisms. Mean pooling provides a general sense of the sentence's semantic content, while max pooling emphasizes the most salient features. Some models also employ hybrid strategies by concatenating both mean and max pooled vectors. Although attention-based pooling has been proposed to assign dynamic importance to tokens [11], simpler pooling mechanisms are often favored in BiLSTM-based models due to their lower computational cost and architectural purity.

Hierarchical NER models have demonstrated strong performance on benchmark datasets such as CoNLL-2003 [1] and OntoNotes 5.0 [17], particularly in tasks requiring long-range context and disambiguation. They are especially effective in handling out-of-vocabulary (OOV) entities and in low-resource settings where local context alone is insufficient. Furthermore, their ability to support nested entity recognition makes them valuable for biomedical, legal, and scientific domains where entities frequently overlap or are embedded within one another [10], [12].

In summary, hierarchical NER architectures extend the capabilities of standard BiLSTM models by modeling linguistic structures at multiple levels. By incorporating sentence- and document-level context into the encoding process, these models achieve more coherent and contextually informed entity recognition, making them well-suited for complex real-world applications.

KEY COMPONENTS IN NER PIPELINES

Modern Named Entity Recognition (NER) pipelines comprise several interdependent components that transform raw input into structured entity labels. While model architecture plays a central role, the design and configuration of other elements—such as embeddings, encoders, decoders, and auxiliary tasks—substantially affect the performance and robustness of a NER system. This section provides a structured overview of these components.

Embedding Strategies

The first step in most NER pipelines is the generation of vector representations for input tokens. Traditional approaches used static word embeddings like Word2Vec, GloVe, and FastText, which map each word to a fixed vector based on distributional statistics from large corpora [5], [6]. Although effective for capturing general semantics, these embeddings cannot adapt to word sense disambiguation or contextual variation.

To address these limitations, many BiLSTM-based models incorporate character-level embeddings. These embeddings are learned using either convolutional neural networks (CNNs) or BiLSTMs over the character sequence of each word [6], [7]. This allows the model to learn morphological features such as affixes and roots, making it particularly robust to rare and out-of-vocabulary (OOV) words. Some models further enhance this by combining word-level and character-level embeddings through concatenation or projection layers, resulting in richer and more informative representations.

Contextual Encoders

Once token embeddings are obtained, the next stage involves encoding their context within the sequence. BiLSTM encoders are widely used for this purpose because they process input in both forward and backward directions, thus capturing bidirectional dependencies in text [4], [5]. This is crucial for resolving ambiguities in entity boundaries and for understanding multi-word expressions.

In hierarchical NER models, contextual encoding is extended beyond individual sentences. Here, word-level BiLSTM outputs are pooled to form sentence vectors, which are then passed through a sentence-level BiLSTM or similar structure [9], [11]. This enables the model to capture inter-sentence dependencies and document-level discourse structures, which are valuable for entity disambiguation in longer texts.

Decoding Mechanisms

After generating context-aware representations for each token, the model must assign entity labels. Two primary decoding mechanisms are prevalent in BiLSTM-based NER: Softmax and Conditional Random Fields (CRFs).

The Softmax decoder predicts labels independently for each token. While this approach is computationally efficient, it may result in label sequences that violate structural constraints—for example, predicting an "I-ORG" tag without a preceding "B-ORG" tag. In contrast, the CRF decoder models the entire sequence of labels jointly, enforcing valid tag transitions and producing globally coherent outputs [4], [6]. This makes CRFs particularly

suitable for structured tagging schemes such as BIO and BILOU.

Auxiliary Modules and Joint Learning

To further enhance performance, some NER systems incorporate auxiliary modules or adopt multi-task learning strategies. A common example is the joint training of NER and Part-of-Speech (POS) tagging, where the model learns shared representations that benefit both tasks. Other approaches include adding sentence-level classifiers that determine whether a sentence contains named entities, thereby reducing the noise passed to the decoder [9].

Such auxiliary modules are particularly beneficial in hierarchical models, where structural information across sentences or paragraphs can be used to refine predictions. Though not always essential, these components can improve generalization, particularly in low-resource settings or domain-specific applications.

Training Objectives and Evaluation Metrics

The most commonly used training objective in NER is the token-level cross-entropy loss, where the model is penalized for incorrect tag predictions on individual tokens. However, this objective may not fully capture the span-level nature of the NER task. As a result, some recent models have explored span-based loss functions or auxiliary supervision at the entity or sentence level [18].

Evaluation of NER models is typically based on Precision, Recall, and F1-score calculated over correctly predicted entity spans. Benchmark datasets such as CoNLL-2003 [1] and OntoNotes 5.0 [17] provide standardized splits for model comparison. To analyze generalization beyond vocabulary overlap, several studies have proposed more nuanced evaluation schemes, such as categorizing tokens into in-vocabulary (IV), out-of-training-vocabulary (OOTV), out-of-embedding-vocabulary (OOEV), and out-of-both-vocabularies (OOBV) groups [18], [19]. These analyses are essential for understanding model robustness, especially in real-world applications with unseen or domain-specific entities.

EVALUATION AND BENCHMARK DATASETS

Evaluating Named Entity Recognition (NER) systems requires standardized datasets, appropriate metrics, and careful consideration of linguistic variability. Benchmark datasets provide the foundation for model comparison, while evaluation protocols assess how well a model can identify and classify entity spans across different scenarios. This section outlines widely used datasets, discusses key evaluation metrics, and highlights evaluation paradigms that address model generalization and robustness.

Benchmark Datasets

The most frequently used datasets for NER evaluation are CoNLL-2003 and OntoNotes 5.0, both of which offer diverse linguistic coverage and standardized evaluation splits.

The CoNLL-2003 dataset [1] consists of English newswire articles from the Reuters corpus and includes annotations for four entity types: Person, Location, Organization, and Miscellaneous. It is widely used due to its clean annotation style, limited domain scope, and established baseline results. CoNLL-2003 has become the de facto standard for evaluating English-language NER systems.

In contrast, OntoNotes 5.0 [17] offers a more comprehensive benchmark, containing multiple genres such as newswire, broadcast news, conversational speech, and web text. It supports a broader label set, including date/time expressions, quantities, events, and more, making it suitable for evaluating general-domain and cross-domain NER systems. OntoNotes also includes nested and overlapping entities, which are increasingly important in complex applications.

Other datasets, such as WNUT (Workshop on Noisy User-generated Text) and GENIA (for biomedical NER), are used in specialized domains. These datasets are valuable for evaluating how well models perform under domain shift, noise, or low-resource conditions.

Evaluation Metrics

NER models are typically evaluated using span-based versions of Precision, Recall, and F1-score. A prediction is considered correct only if the predicted entity span and label exactly match the ground truth.

- Precision (P) measures the proportion of predicted entities that are correct.
- Recall (R) measures the proportion of ground truth entities that are correctly predicted.
- F1-Score (F1) is the harmonic mean of precision and recall, providing a single measure that balances both.

These metrics are often reported on the test split of benchmark datasets, using official evaluation scripts to ensure consistency across studies.

For sequence-level labeling models (e.g., BiLSTM-CRF), metrics may also be broken down by entity type (e.g., PER, LOC, ORG) to reveal which categories are most challenging. Some works additionally report token-level accuracy, though this is less informative for span-based tasks.

Robustness: IV, OOV, and Vocabulary-Based Analysis

While aggregate metrics such as F1-score are helpful, they can obscure performance disparities on different categories of words. To address this, several studies have proposed evaluation frameworks that assess generalization beyond the training vocabulary [18], [19].

Tokens can be grouped into the following categories:

- IV (In-Vocabulary): Tokens seen during training and present in the embedding vocabulary.
- OOTV (Out-of-Training Vocabulary): Tokens present in the embedding vocabulary but not seen during training.
- OOEV (Out-of-Embedding Vocabulary): Tokens seen in training but not present in the embedding vocabulary.
- OOBV (Out-of-Both Vocabulary): Tokens neither seen in training nor present in embeddings.

Evaluating model performance across these categories offers deeper insight into robustness, particularly for handling rare entities, domain shifts, and noise. Hierarchical and character-enhanced models often outperform baseline BiLSTM models in OOTV and OOBV categories due to their ability to generalize beyond surface form memorization.

Span-Level vs. Token-Level Evaluation

NER is inherently a span-based task, yet some models (particularly those with Softmax decoders) are trained and evaluated at the token level. This mismatch can result in inflated token accuracy that does not reflect span-level correctness. Consequently, recent efforts have emphasized the importance of span-F1 evaluation, where precision and recall are computed over entire entity spans.A

COMPARATIVE ANALYSIS

A diverse array of NER architectures—ranging from flat BiLSTM models to hierarchical and transformer-based systems—have been proposed to address the challenges of entity recognition in varied linguistic and domain-specific contexts. This section presents a comparative analysis of these models by examining their design characteristics, evaluation performance, and strengths across different categories, particularly under varying vocabulary and context constraints.

Architecture-Level Comparison

The first axis of comparison is architectural design. While traditional BiLSTM-CRF models operate at the word-sequence level, hierarchical variants introduce additional sentence-level encoders. Transformer-based models rely on self-attention mechanisms and pretraining for contextualization.

Table 8. Comparison of Key NER Model Architectures

Model Type	Architecture	Context Scope	Decoder Type	Reference
BiLSTM-CRF	Word-level BiLSTM + CRF	Intra-sentence	CRF	[4], [6]
BiLSTM-CNN-CRF	Word + Char CNN embeddings	Intra-sentence	CRF	[6], [7]
Hierarchical BiLSTM	Word + Sentence-level BiLSTMs	Cross-sentence	CRF / Softmax	[9], [11]
Transformer-based NER	Self-attention (e.g., BERT)	Sentence + Document	Softmax	[13], [14]

As shown, hierarchical models expand the context window by incorporating sentence-level representations, whereas transformer-based models extend this further through global self-attention.

Performance Across Vocabulary Categories

BiLSTM models typically perform well on in-vocabulary (IV) tokens but experience degradation when encountering out-of-vocabulary (OOV) cases. Hierarchical and subword-aware models mitigate this through multi-level encoding and character-level modeling.

Table 9. Relative Performance Across Vocabulary Categories (Qualitative Summary)

Model	IV	OOTV	OOEV	OOBV
BiLSTM-CRF	High	Medium	Low	Low
BiLSTM + Char Embedding	High	High	Medium	Medium

Hierarchical BiLSTM	High	High	High	Medium
Transformer-based NER	Very High	High	High	High

Hierarchical and character-enhanced BiLSTM models offer improvements in OOTV and OOEV categories, while transformers achieve superior performance in general but at significantly higher computational cost.

Strengths and Trade-offs

A comprehensive evaluation requires considering trade-offs between performance, interpretability, computational efficiency, and generalization. The following table summarizes these trade-offs:

Table 10.Strengths and Limitation of Major NER Architectures

Model Type	Strengths	Limitations
BiLSTM-CRF	Simplicity, strong baseline performance	Weak in long-range dependencies
BiLSTM + Char Embedding	Robust to rare and morphologically complex tokens	Increased training time
Hierarchical BiLSTM	Better document-level coherence, disambiguation	Sentence segmentation overhead, model complexity
Transformer-based NER	High accuracy, long-range modeling	High memory usage, less interpretable

The selection of an appropriate model architecture depends heavily on the application scenario. For short texts and constrained environments, BiLSTM-CRF variants remain viable. Hierarchical models are more suited for longer documents or tasks requiring discourse-level consistency. Transformer models are effective for high-resource tasks but are often impractical for deployment in latency- or memory-sensitive applications.

Dataset-Specific Observations

Performance trends can also be observed across different benchmark datasets. On CoNLL-2003, which comprises relatively short and clean newswire text, most models perform well, and the margin between BiLSTM and transformer models is relatively small. However, on OntoNotes 5.0, which includes conversational data and longer documents, hierarchical and transformer-based models exhibit greater improvements due to their ability to model broader context [17].

Table 11. Architecture Trends by Dataset

Dataset	Best Performing Model Type	Key Considerations
CoNLL-2003	BiLSTM-CRF, BERT-based NER	Short, clean sentences; label consistency
OntoNotes 5.0	Hierarchical BiLSTM, Transformers	Long text, domain and genre diversity
WNUT / Biomedical	Char-enhanced or Hierarchical NER	Noisy, domain-specific entities

These observations confirm that hierarchical BiLSTM models provide a viable and efficient middle ground between traditional BiLSTM systems and resource-intensive transformer models.

CHALLENGES AND OPEN ISSUES

Despite substantial progress in Named Entity Recognition (NER), a number of critical challenges remain unresolved. These challenges span across architectural limitations, linguistic complexities, data availability, and deployment constraints. This section outlines key open issues that continue to shape research directions in the field, particularly in the context of BiLSTM-based and hierarchical NER models.

Generalization to Low-Resource and Domain-Specific Settings

One of the most pressing challenges in NER is achieving robust performance across domains, especially in low-resource settings where annotated data is scarce or domain-specific terminology diverges from general corpora. While BiLSTM models with character-level encodings improve generalization to some extent [6], [7], they still struggle when transferred to domains such as biomedical, legal, or conversational text. Domain adaptation techniques, including unsupervised pretraining and fine-tuning, have shown promise, but require further investigation to ensure stability and data efficiency.

Additionally, cross-lingual NER remains a challenge, particularly for morphologically rich or low-resource languages. Multilingual models and zero-shot transfer techniques are being explored, but existing BiLSTM-based systems often lack the flexibility needed for such tasks without significant retraining or parallel corpora.

Handling Nested and Overlapping Entities

Standard sequence labeling approaches are inherently linear and are thus ill-suited for recognizing nested or overlapping entities, which are common in biomedical

texts and legal documents. While hierarchical or layered models have been proposed to address this [10], [12], these approaches often introduce architectural complexity and require custom training regimes. There remains a need for lightweight yet accurate models that can naturally handle such structural phenomena without compromising sequence coherence or computational efficiency.

Modeling Long-Range Dependencies Without Transformers

One of the principal motivations for hierarchical BiLSTM models is to address the limited context window of standard sequence encoders. However, most hierarchical approaches rely on sentence segmentation and pooled representations, which can still lose inter-sentence coherence or overlook dependencies that span paragraphs. While transformers have demonstrated superior capacity for long-range modeling [13], [14], they introduce high memory and inference costs, limiting their practical applicability.

A significant open question is how to improve long-range dependency modeling within BiLSTM frameworks without introducing full self-attention mechanisms. Future work may explore optimized recurrent architectures, residual contextual bridges, or light global representations that preserve efficiency while enhancing semantic cohesion.

Evaluation Limitations and Metric Gaps

Most existing evaluation frameworks for NER focus on exact match span-based F1 scores, which, although informative, may not fully reflect a model's ability to generalize across vocabulary, handle ambiguous mentions, or disambiguate entity types in context [18], [19]. More nuanced metrics, such as category-wise breakdowns (IV, OOTV, OOBV), span-F1 with partial overlap, or entity linking performance, are necessary to assess real-world effectiveness.

Moreover, current evaluation protocols often assume a single correct annotation per entity, which is not always valid in conversational or multi-annotator settings. Thus, designing evaluation methods that account for annotation variability and partial correctness remains an open research direction.

Scalability and Real-Time Deployment

Many state-of-the-art models are difficult to deploy in production environments due to their high latency, memory consumption, or hardware dependence. BiLSTM-based systems offer better efficiency than transformers but still pose challenges in real-time processing, particularly when hierarchical components are used. The development of lightweight, scalable NER models that maintain competitive accuracy while reducing computational overhead is an important direction for applied NER research.

Additionally, incremental learning and online adaptation—where models can update continuously without full retraining—are increasingly necessary in dynamic applications like customer service, financial monitoring, and social media analytics.

Interpretability and Debugging

As NER models are increasingly used in high-stakes applications (e.g., healthcare, finance, legal domains), the interpretability of predictions becomes crucial. While BiLSTM architectures are more interpretable than transformer models due to their sequential structure, understanding decision pathways—especially in hierarchical models—remains non-trivial. There is a need for transparent diagnostic tools that can visualize context influence, trace label propagation, and detect erroneous dependencies, thereby facilitating better human-model interaction and trust.

FUTURE DIRECTIONS

Despite the progress achieved by BiLSTM-based and hierarchical models in Named Entity Recognition (NER), several avenues remain open for further exploration. A key direction involves the development of lightweight hierarchical architectures that maintain contextual depth while reducing computational overhead. Such models would be particularly useful in real-time or resource-constrained applications.

The integration of span-based decoding strategies with traditional sequence labeling could enhance the handling of overlapping and nested entities, which are common in biomedical and legal texts. Additionally, self-supervised and weakly supervised learning methods can help mitigate the scarcity of annotated data, especially in domain-specific or low-resource settings.

Another important area is multilingual and cross-lingual NER, where BiLSTM models could be extended using shared character-level encoders or multilingual embeddings. Supporting continual learning—where models incrementally adapt to new entity types or domains—is also crucial for long-term deployment.

Finally, improving model interpretability, developing user-controllable tagging systems, and expanding evaluation to include robustness, efficiency, and adaptability will ensure that future NER systems are not only accurate but also practical and trustworthy.

CONCLUSION

Named Entity Recognition (NER) remains a critical task in Natural Language Processing, underpinning a wide range of applications from information extraction to knowledge graph construction. This survey has reviewed the evolution of NER models, tracing the shift from rule-based and statistical approaches to neural architectures—particularly BiLSTM-based and hierarchical frameworks.

BiLSTM-based models have demonstrated strong performance by effectively capturing local contextual dependencies and integrating character-level representations to handle rare or unseen tokens. Building on these foundations, hierarchical models have introduced multi-level context encoding, enabling better modeling of long-range dependencies and discourse-level coherence. These architectures have proven especially useful for complex scenarios, such as nested entities and multi-sentence documents, offering a strong alternative to transformer-based systems in contexts where interpretability, modularity, and computational efficiency are essential.

Through comparative analysis, we have highlighted the trade-offs between model complexity, performance, and deployment feasibility. Hierarchical BiLSTM models offer a compelling balance, achieving strong results on standard benchmarks while remaining accessible for deployment in constrained environments.

Despite these advancements, several challenges remain, including limited generalization in low-resource domains, the difficulty of modeling nested or overlapping entities, and the need for more robust evaluation frameworks. Future research must address these challenges through architectural innovations, self-supervised learning strategies, and improved interpretability.

In conclusion, BiLSTM-based and hierarchical NER models continue to be foundational in the design of practical and adaptable entity recognition systems. As the field moves toward more robust, multilingual, and context-aware solutions, these architectures will remain highly relevant, serving as both strong baselines and platforms for future innovation.

REFERENCES

1. E. F. Tjong Kim Sang and F. De Meulder, “Introduction to the CoNLL-2003 shared task: Language-independent named entity recognition,” in Proc. CoNLL, 2003, pp. 142–147.
2. McCallum and W. Li, “Early results for named entity recognition with conditional random fields, feature induction and web-enhanced lexicons,” in Proc. HLT-NAACL, 2003.
3. J. Lafferty, A. McCallum, and F. Pereira, “Conditional random fields: Probabilistic models for segmenting and labeling sequence data,” in Proc. ICML, 2001, pp. 282–289.
4. Z. Huang, W. Xu, and K. Yu, “Bidirectional LSTM-CRF models for sequence tagging,” arXiv preprint arXiv:1508.01991, 2015.
5. G. Lample, M. Ballesteros, S. Subramanian, K. Kawakami, and C. Dyer, “Neural architectures for named entity recognition,” in Proc. NAACL-HLT, 2016, pp. 260–270.
6. X. Ma and E. Hovy, “End-to-end sequence labeling via bi-directional LSTM-CNNs-CRF,” in Proc. ACL, 2016, pp. 1064–1074.
7. J. P. C. Chiu and E. Nichols, “Named entity recognition with bidirectional LSTM-CNNs,” Trans. ACL, vol. 4, pp. 357–370, 2016.
8. Y. Lin, H. Ji, Z. Liu, and M. Sun, “A multi-level contextualized representation for fine-grained entity typing,” in Proc. ACL, 2019, pp. 283–290.
9. Z. Zhang and H. Wang, “Hierarchical attention network for NER in long documents,” in Proc. AAAI, 2018.
10. M. Ju, M. Miwa, and S. Ananiadou, “A neural layered model for nested named entity recognition,” in Proc. NAACL-HLT, 2018, pp. 1446–1459.
11. L. Luo, Y. Yang, P. Zhang, H. Lin, Z. Yang, and J. Wang, “Hierarchical contextualized representations for named entity recognition,” in Proc. AAAI, 2020, pp. 8449–8456.
12. J. Straková, M. Straka, and J. Hajič, “Neural architectures for nested NER through linearization,” in Proc. ACL, 2019, pp. 5326–5331.
13. J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “BERT: Pre-training of deep bidirectional transformers for language understanding,” in Proc. NAACL-HLT, 2019, pp. 4171–4186.
14. Y. Liu et al., “RoBERTa: A robustly optimized BERT pretraining approach,” arXiv preprint arXiv:1907.11692, 2019.
15. Y. Xu, Y. He, K. Zhang, W. Sun, and Z. Liu, “Entity-context relation enhanced BERT for named entity recognition,” in Proc. ACL, 2020, pp. 792–802.
16. X. Wang, C. Yu, Y. Lai, and S. Dai, “TENER: Adapting transformer encoder for named entity recognition,” arXiv preprint arXiv:2009.07659, 2021.
17. R. Weischedel et al., “OntoNotes Release 5.0,” Linguistic Data Consortium, Philadelphia, 2013.
18. Y. Lin et al., “A rigorous study of NER performance across out-of-vocabulary settings,” in Proc. COLING, 2020, pp. 6262–6274.
19. N. Reimers and I. Gurevych, “Reporting score distributions makes a difference: Performance study of NER models,” in Proc. EMNLP, 2017, pp. 338–348.

Analyzing Machine Learning Methodologies towards Efficient Real Estate Price Prediction

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ABSTRACT

Accurate estimation of house prices is a prime task that influences the strategies of various players in the property business, such as investors, policymakers, home buyers and sellers. The research has been done on two diverse locations, Gurgaon - Haryana and Boston- Massachusetts. The dataset is designed to provide insights into the vast majority of property markets world-wide since it captures various details about them. The research uses machine learning algorithms that can generate accurate pricing models for investing in properties. The research has developed the models to ensure they accurately predict values of housing units across a wide range of attributes such as size, amenities, and location, which are all based on vital economic indicators. Leading-edge feature engineering and selection techniques improve model reliability and interpretability to capture subtle variations within real estate dynamics. This research enables those interested in the investment and valuation of real estate to make better decisions. Furthermore, this study examines the major determinants that affect housing prices in the real estate market. Random forest and multivariate regression were found to be the best-performing models for the Boston and Gurgaon datasets, respectively. For the Boston dataset, the MAE ranged from 0.8137 to 3.4006, RMSE ranged from 1.1634 to 4.8353, and R2 score ranged from 0.9846 to 0.7339. For the Gurgaon dataset, the MAE ranged from 1.91 to 2.57, RMSE ranged from 2.46 to 3.61, and R2 score ranged from 0.955 to 0.905.

***KEYWORDS** : Real estate price prediction, Machine learning algorithms, Feature selection, Predictive modeling, Ensemble learning, Housing market forecasting.*

INTRODUCTION

Machine learning (ML) is now an integral part of modern industry and research, with computer system performance constantly being improved using algorithms and neural network models. For this reason, ML algorithms use sample data called 'training data' to automatically build mathematical models that make decisions without any given program instructions. Fair assessment is a must have for the real estate industry where buyers seek properties for personal residence or investment while agencies engage in property sales relating to businesses. Nonetheless, it remains challenging to determine whether house is over-priced or under-priced primarily because very few well-established detection methods are available. Although some indicators such as house price-to-rent ratios provide a preliminary idea, deeper scrutiny is required before one can make well-informed choices.

With the availability of large datasets for training, machine learning becomes a viable approach for generating accurate pricing forecasts tailored to user demand. The objective of these initiatives is to serve users effectively by utilizing multiple machine learning techniques and integrating them into models that help buyers find homes with their desired features at an affordable price. Meanwhile, vendors hope to come up with a fair asking price for their houses. This calls for careful examination to avoid underpricing or overpricing. Buyers and sellers can secure transactions and reduce the risk of undervaluation and overvaluation using ML-backed price projections to guide their choices. This study aims to bridge the gap between traditional real estate practices and state-of-the-art machine learning techniques to equip stakeholders with the tools they need to make optimal decisions amidst constantly changing real estate market dynamics.

LITERATURE ANALYSIS

The task of forecasting real estate prices accurately has grabbed significant attention in both academic research and industry practice, as it directly supports better decision-making by investors,developers,policymakers, and homebuyers. Over time, the focus of this research has evolved from traditional statistical models to sophisticated machine learning (ML) and ensemble approaches that address the complex, nonlinear nature of property markets.

Early studies predominantly relied on regression-based techniques to understand the relationship between housing prices and explanatory variables. Granger and Pesaran highlighted challenges such as regional dynamics, market sentiment, and macroeconomic influences that complicate price forecasting [4]. Similarly, Geltner and Miller emphasized the growing need for reliable predictive models in the face of globalization and increasingly interconnected markets [3].

With the advent of machine learning, researchers began to explore more flexible and robust techniques. Ensemble models like Random Forest, Gradient Boosting, and XGBoost have gained popularity due to their ability to handle complex interactions between features while minimizing overfitting. Wang and Liu demonstrated how ensemble learning approaches including bagging, boosting, and stacking - can enhance predictive accuracy in diverse real estate market conditions [11]. Ravikumar also found Random Forest to be particularly effective in housing price prediction tasks, offering practical benefits for both individual and institutional decision-making [10].

Feature engineering and selection have emerged as critical steps in improving model performance. Wang et al. and Lian et al. emphasized that incorporating domain knowledge through engineered features (e.g., proximity to amenities, crime rates, environmental quality) significantly boosts model reliability [12], [8]. This is supported by Yu and Wu, who demonstrated that Support Vector Regression (SVR) effectively captures the influence of key attributes like neighborhood quality and property size [13].

Researchers have also increasingly integrated macroeconomic indicators (e.g., GDP growth, interest rates, inflation) alongside property-specific factors to build more comprehensive forecasting models. Johnson et al. proposed frameworks combining both micro- and macro-level variables, leading to models better suited to dynamic market environments [6].

Recent studies have explored hybrid models and the incorporation of additional data dimensions such as geospatial patterns and temporal trends. Chen et al. and Dabreo et al. illustrated that combining multiple models or incorporating user-friendly interfaces can further improve prediction performance and usability [1], [2]. Muralidharan et al. highlighted the significance of external factors like crime rates in affecting housing prices, calling for richer datasets and more holistic models [9].

In summary, the literature suggests a clear progression towards advanced machine learning techniques, particularly ensemble and hybrid models, for real estate price prediction. However, gaps remain in terms of generalizability across regions, model interpretability, and the incorporation of broader economic and spatial factors. Our study seeks to contribute to this evolving field by comparing various machine learning methodologies on diverse datasets and identifying the key determinants influencing real estate prices in distinct markets.

LIMITATIONS FOR PREVAILING TECHNOLOGIES

Data availability and quality: It is often said that this field of research has some major challenges including the accuracy of housing price forecasts. Nevertheless, Data Camp and Kaggle platforms may not have enough particulars or all elements needed to determine property worth. In such a case, it is better to use data with high quality for accurate predictions.

Model Interpretability: The development of machine learning does not lead to more understandable forecasting models like real estate price prediction models. They could be “black boxes” where those in volved or other institutional members cannot see be yond their projections. Lack of interpretability can result in mistrust.

Generalization and Transferability: Another problem with current state-of-the-art technology is that predictive modeling doesn’t work across different local real estate markets. These prediction models are expected to perform poorly if applied in completely new areas having different attributes and dynamics.

The intricacy and expandability of computers: The machine learning algorithms that automate real estate pricing predictions must be complex and scalable, thus time-consuming and requiring special skills. This might make it difficult for predictive models to be adapted in terms of computing cost, especially among non-computerized people.

Considering the current research tools applicable to recent circumstances regarding real estate price prediction, one should concentrate on ethical issues, legal aspects concerning data privacy, security and compliance. In these processes they can handle sensitive and confidential information which raise moral questions such as whether user data privacy rights are being violated or data protection legislations in fringed. All stakeholders should observe best practices and relevant legal frameworks related to property transactions to achieve transparency, equity or fair ness, responsibility when using predictive modeling techniques into property markets. Meanwhile ignoring the ethical as well as the regulatory dimensions while implementing ML-aided methods for forecasting real estate housing costs could have legal consequences.

PROPOSED WORK

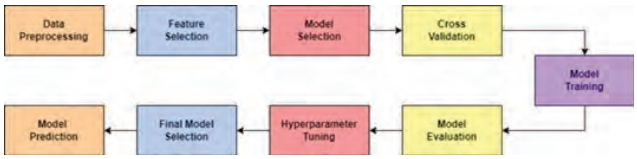

Fig. 1 : Block Diagram of Proposed System

As shown in Figure (1), model will be created that will predict the house prices using machine learning by taking into account different characteristics. The development of this model is expected to include the following steps:

Data Collection: The first step is to identify a suit able dataset that includes features which can assist in getting the selling price of homes. It should be inclusive and have things like home size, number of rooms, bathrooms, location among other pertinent things.

Data Preprocessing: The data set will then be pre-processed until it is ready for training or testing purposes. This means taking out any outliers and missing values from it.

Feature Selection: Then we select features that help train our model most efficiently by looking at the correlations between each feature and house prices. Based on their coefficient value; top features are selected from this process. Feature selection techniques like SelectKBest and chi-square can also be employed to extract the top features.

Model Selection: Several machine learning models will then have to be trained using those selected features while their performance is assessed. Then, during evaluation, best performing model would make it through selection for deployment.

Cross-Validation: To validate the selected model, a cross-validation will be employed to guarantee its generalization capability to new data. Cross validation helps us in reducing the overfitting factor from the machine learning model and ensures that the accuracy of house price prediction is intact.

Model Training: The selected model later will be trained on the training dataset which is obtained from splitting the entire dataset into and its performance will be evaluated.

Model Evaluation: The performance metrics for the trained model includes evaluating mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE) and R-squared (R2) score which is achieved by comparing the predictions of the model with the value of independent variable of testing dataset.

Hyperparameter Tuning: Fine-tuning will be per formed on the hyperparameters of the chosen model in order to enhance its performance and accuracy.

Final Model Selection: This final model will be chosen depending on how well the machine learning model performs on the validation set.

The research work will be based on the traditional machine learning approach consisting two parts specifically: the training and testing. The label, input, feature extractor as well as machine learning algorithm are some of the elements of this section. Input, feature extractor, regression model and output label are some of the components of this section.

The input is a collection of information from different sources while feature extractor is used to ex tract only important features that affect prediction results. Afterward, these features are pre-processed to achieve normalized dataset and data row labelling is done. Once training dataset's outcome is fed into machine learning algorithm's input, ML Algorithm result is entered into Regression model contributing trained model or trained regressor. This trained regressor can predict the output label by applying the newly extracted characteristic from the test data as an input.

DATASET ANALYSIS

Datasets

The research have used two datasets for this research and a variety of machine learning algorithms that are already on the market to foresee pricing of real estate properties, specifically houses.

A. The UCI Machine Learning Repository provided the first dataset, which is about suburban Boston house values. This dataset was first gathered via Carnegie Mellon University's StatLib library. The following table depicts the list of variables required to build the prediction model. In order to foresee or predict house values, this study uses thirteen characteristics as distinct variables as described in Table 1.

Table 1 : Attributes and Descriptions (Boston)

Attributes	Description
MEDV	Owner-occupied home median value in the $10,000s
B	1000 (Bk - 0.63) ^2 Where Bk Is the Town-Level Black Population Proportion
TAX	Property's Whole Value and Tax Rate Per $10000
DIS	weighted distances to five employment centers in Boston
RM	Average Room Count per Household
CHAS	Dummy variable Charles River (= 1 if Tract Bounds River, 0 otherwise)
ZN	Residential land zoned for lots larger than 25,000 square feet.
LSTAT	Percentage of Lower Status Population
PTRATIO	Town-Level Pupil-Teacher Ratio
RAD	Radial Highway Accessibility Index
AGE	The percentage of owner-occupied residences constructed before 1940
NOX	Concentration of Nitric Oxides (Parts per 10 Million)
INDUS	Ratio of Non-Retail Commercial Acres in Each Town
CRIM	Town-Level Per capita crime rate

The second dataset, which relates to house values in Gurugram is taken from Kaggle which is data from 99acres.com uploaded by Anshul Raj Verma. For the forecast of house prices in Gurugram, we have taken consideration of five key factors which influence the price which is described in Table 2.

Table 2 : Attributes and Descriptions (Gurgaon)

Attributes	Description
Carpet Area	Total area within the walls of the property that can be covered
Bedroom	Total number of bedroom(s) in the property
Bathroom	Total number of bathroom(s) in the property
Balcony	Total number of balcony (outdoor area) in the property
Floor	Level on which the property is located with respect to ground
Price	The price of the property

Data Cleaning

There were only 5 missing records in dataset of Boston city, which were dropped and the Gurugram dataset that had a lot of missing values in the price column comparatively were also dropped as they were less than 5% of the entire dataset and corresponding carpet area also acted as outliers.

Correlation Between Attributes

Correlation co-efficient between the attributes gives us the idea of strength of the relationship between them, whether they are positively or negatively correlated or there exists no correlation between them at all. This can be viewed as the following for 'r' values:

- $0 < r \leq 1$ indicates positive correlation
- $r = 0$ indicates no correlation
- $-1 \leq r < 0$ indicates negative correlation

Table 3 : Correlation table of Boston dataset

Features	R Value
MEDV	1.000000
RM	0.696169
ZN	0.360445
B	0.333461
DIS	0.249929
CHAS	0.175260
AGE	-0.376955
RAD	-0.381626
CRIM	-0.388305
NOX	-0.427321
TAX	-0.468536
INDUS	-0.483725
PTRATIO	-0.507787
LSTAT	-0.737663

It is quite evident from Table 3 that RM (number of rooms) and ZN are the two most significantly correlated features, whereas LSTAT and PTRATIO are least significantly correlated features. This simply indicates that the price of a house would rise in a situation when the RM or Z values increases and would fall in case, values of PTRATIO or LSTAT increases.

Table 4 : Correlation table of Gurgaon dataset

Features	R Value
NewPrice	1.000000
CarpetArea	0.979041
bedroom	0.613400
bathroom	0.584807
balcony	0.342652
Floor	0.066435

It can be clearly seen from Table 4 that CarpetArea (total area in sq.ft of property) is highly positively correlated followed by bedRoom (No of bedrooms). This means that if value of CarpetArea or/and bedroom increases, the price of the property would also increase considerably. There is no attribute which is negatively correlated with Price in Gurugram dataset.

The heatmap helps in simple visual representation of how the features are correlated– positively or negatively along with the strength. In heatmap, the value of 'r' is rounded-off to the nearest 2-decimal integer.

The following Figure (2) shows that RM and MEDV has highest positive correlation coefficient (r = 0.70) and highest negative correlation coefficient (r = -0.74) is seen between LSTAT and MEDV.

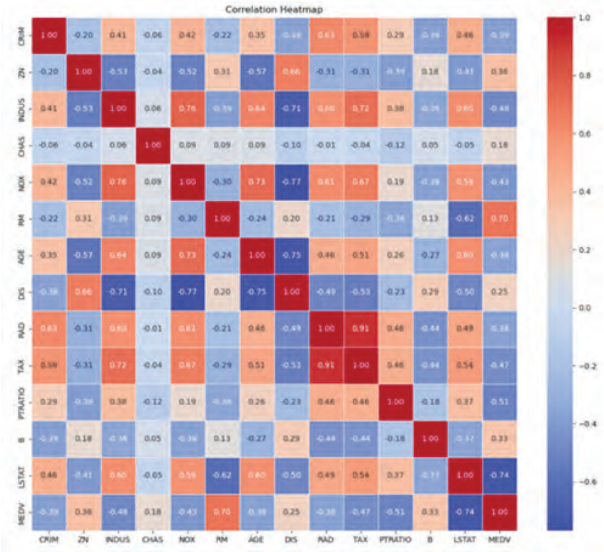

Fig. 2 : Correlation Heatmap for Boston dataset

The following Figure (3) shows that CarpetArea and Price has highest positive correlation coefficient (r = 0.98) and lowest positive correlation coefficient (r = 0.066) is seen between Floor and Price.

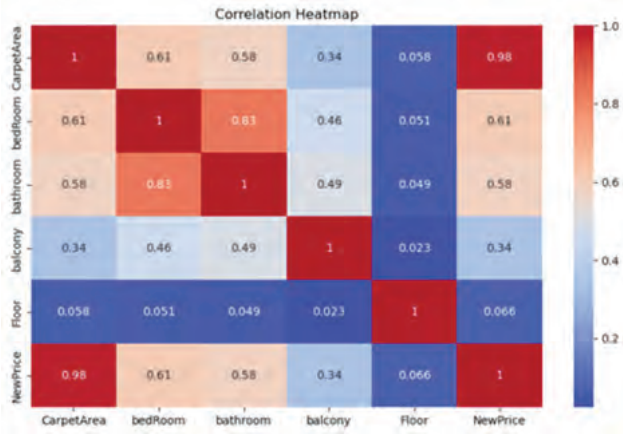

Fig. 3 : Correlation Heatmap for Gurgaon dataset

FEATURE SELECTION

For effective analysis of data and accurate predictions, it is very important to determine the most important features which affect the independent variable in the dataset which is price of the house in our case. These are the qualities that help us build accurate and reliable models.

Various methods are used by SelectKBest to determine the relationship between features and the output variable. These statistical approaches include chi square test, ANOVA F-test and mutual information score. The selection process involves ranking them before identifying the K highest scoring ones for inclusion in a final feature subset.

Chi-Square is used in statistics to test the in dependence of two events. It is calculated from the formula shown in equation (1) where O = observed value and E = expected value.

$$X_c^2 = \frac{\sum_i^n (O_i - E_i)^2}{\sum_i^n (E_i)^2} \qquad (1)$$

If two characteristics are independent, their ob served count tends toward equaling expectancy so we will end up with smaller values of Chi-Square. To put it differently, a feature can be chosen for training models if there is higher value of Chi-Square which shows that it depends on response more.

After applying SelectKBest and chi-square (chi2) methods on the Boston housing dataset which aims at predicting house prices in Boston region, we came up with the following predictors:

I. CRIM

II. ZN

III. TAX

After applying SelectKBest and chi-square (chi2) methods on the Gurugram housing dataset which aims at predicting house prices in Gurugram region, we came up with the following predictors:

I. CarpetArea

II. Balcony

III. Floor

RESULTS – EVALUATION METRICS

The evaluation metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), R2 Score and mean cross-validation score for six distinct ma chine learning models, are shown in the following two tables for the Boston and Gurugram datasets. The following table makes it easier to choose which machine learning model is best for predicting property prices.

For Boston dataset shown in the following Table 5, the best accuracy has been provided by Random Forest algorithm closely followed by Gradient Boosting and then by Xtreme Gradient Boosting (XGBoost) algorithm. Multi-variate (linear regression) stands at the last position for accuracy as compared to the other machine learning algorithms used for Boston dataset. Additionally, by assessing these values using the cross-validation technique, all of the model predictions were cross-checked for overfitting. As a result, these scores are very precise. The metrics for Random Forest algorithm which stands as the best model are such that MAE is 0.8137; RMSE is 1.1634; R2 score of 0.9846 which indicates 98.46% accuracy and mean cross-validation score is 0.7413. A very excellent fit between the model and the real data is indicated by the R2 score and mean cross-validation score. After Random forest model, the best performing model is Gradient Boosting whose MAE is 1.0766; RMSE is 1.3649; R2 score is 0.9788 and mean cross validation is 0.7348. The metrics for Multivariate Regression model which stands at the last position are such that MAE is 3.4006; RMSE is 4.8353; R2 score of 0.7339 and mean cross validation score of 0.7351.

Table 5 : Boston Dataset (in millions)

Algorithm	MAE	RMSE	R^2	Mean cross Validation Score
Random Forest	0.81	1.16	0.984	0.741
Gradient Boosting	1.07	1.36	0.978	0.735
XG Boost	1.12	1.43	0.976	0.754
KNN	2.62	3.86	0.799	0.650
Decision Tree	2.78	4.13	0.769	0.704
Regression	3.40	4.83	0.734	0.735

For Gurugram dataset shown in the following Table 6, the best accuracy has been provided by Multi-variate Regression (Linear regression) closely followed by Gradient Boosting and then by K-Nearest Neighbour (KNN) algorithm. Decision Tree algorithm stands at the last position for accuracy as compared to the above mentioned machine learning algorithms for Gurugram dataset but only with slight differences. Additionally, by assessing these values using the cross-validation technique, all of the model predictions were cross-checked for overfitting. As a result, these scores are very precise. The metrics for Multivariate Regression model which stands as the best model are such that MAE is 1.91; RMSE is 2.46; R2 score of 0.955 which indicates 95.5% accuracy and mean cross validation score of 0.956. The 2nd best model is Gradient Boosting whose MAE is 1.92; RMSE is 2.49; R2 score is 0.955 and mean cross validation score is 0.941. The metrics for Decision Tree algorithm which stands at the last position are such that MAE is 2.57; RMSE is 3.61; R2 score of 0.905 which indicates 90.5% accuracy and mean cross-validation score is 0.902. The R2 score also matches with mean cross-validation score for Gurugram dataset indicating a highly reliable and well-performing model.

Table 6 : Gurgaon dataset (in millions)

Algorithm	MAE	RMSE	R2	Mean cross Validation Score
Regression	1.91	2.46	0.955	0.956
Gradient Boosting	1.92	2.49	0.955	0.941
KNN	2.05	2.81	0.943	0.904
Random Forest	2.13	2.85	0.941	0.926
XG Boost	1.97	3.07	0.931	0.903
Decision Tree	2.57	3.61	0.905	0.902

CONCLUSION

The final chapter of the research paper describes in detail predictive modeling methods used to estimate real estate values of Boston and Gurugram. Also, there have been

implemented various machine learning algorithms, feature selection approaches and cross-validation techniques to build accurate models that predict real estate values based on certain key attributes. We were able to identify the key determinants of property value in two areas after having adequately tested and analyzed both datasets; an insightful information to investors, sellers, lawmakers, urban planning bodies and real estate industry players. The generated models exhibit high predictive performance that gives useful insights into how the housing market functions as well as support well-informed decisions. The top two models for Boston dataset are Random Forest and Gradient Boosting with 98.46% and 97.88% accuracy respectively. While, the top two models for Gurgaon dataset are Multivariate regression and Gradient Boosting with 95.5% accuracy of both the models. The links to the dataset used for analysis of machine learning methodologies for efficient real estate price prediction are as follows:

i. https://www.kaggle.com/datasets/schirmerchad/bostonhoustingmlnd

ii. https://www.kaggle.com/datasets/arvanshul/gurgaon-real-estate-99acres-com

FUTURE SCOPE

Future research may therefore consider more complicated modeling approaches or additional data sources or handle temporal and spatial dimensions so as to enhance model accuracy and its applicability. In conclusion, this investigation contributes to the growing body of knowledge on data-driven decision making in real estate markets. To help in this regard, more insights into how the housing market operates will be gained if we take an interdisciplinary approach and adopt current methodologies. In future, it would be interesting to explore more elaborate modeling approaches, use additional data sources, or address temporal and spatial concerns so as to enhance the accuracy and relevance of such models. It is another proof that shows how use of data to make decisions looks like in an existing real estate market analysis. Through employing multiple disciplines and advanced methods, we can best understand market dynamics in housing sector and overcome industry challenges.

REFERENCES

1. J. Chen, L. Song, C. Weng, Y. Zhang, and H. Zhao, "A predictive model of house prices in China," Journal of Housing Economics, vol. 31, pp. 14–26, 2016.
2. S. Dabreo, S. Rodrigues, V. Rodrigues, and P. Shah, "Real estate price prediction," International Journal of Engineering Research & Technology (IJERT), vol. 10, no. 4, pp. 2278–0181, 2021.
3. D. Geltner and N. G. Miller, Commercial Real Estate Analysis and Investments. South Western Cengage Learning, 2001.
4. C. W. J. Granger and M. H. Pesaran, "Economic and statistical measures of forecast accuracy," Journal of Forecasting, vol. 19, no. 8, pp. 537–560, 2000.
5. Z. Huang, J. Zhang, L. Chen, and Y. Yang, "Real estate price prediction with a hybrid model," Sustainability, vol. 11, no. 18, p. 5118, 2019.
6. M. Johnson, D. Smith, and K. Brown, "Integration of economic indicators in real estate price prediction models," Journal of Property Research, vol. 33, no. 2, pp. 185–200, 2016.
7. Z. Li, Y. Wu, G. Wang, L. Wang, and D. Huang, "A comprehensive review of data mining research on the selection of indicators in the prediction of real estate prices," Sustainability, vol. 9, no. 11, p. 2124, 2017.
8. J. Lian, Z. Tian, W. Kang, and C. Zhang, "Housing price prediction: A review," Sustainability, vol. 12, no. 3, p. 974, 2020.
9. S. Muralidharan, K. Phiri, S. K. Sinha, and B. Kim, "Analysis and n of real estate prices: A case of the Boston housing market," Issues in Information Systems, vol. 19, no. 2, pp. 109–118, 2018.
10. A. S. Ravikumar, Real estate price prediction using machine learning, PhD dissertation, National College of Ireland, Dublin, 2017.
11. H. Wang and X. Liu, "Ensemble learning approaches for real estate market analysis," Expert Systems with Applications, vol. 56, pp. 18–32, 2017.
12. Y. Wang, L. Zhang, C. Chen, and X. Zhang, "House price prediction: Parametric versus semiparametric spatial hedonic models," Habitat International, vol. 71, pp. 126–137, 2018.
13. H. Yu and J. Wu, "Real estate price prediction with regression and classification," CS229 (machine learning) Final project reports, 2016.

Building Autonomy in Ecommerce platforms through Agentic AI Techniques

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ABSTRACT

The fast-growing digital business environment requires platforms, which in addition to scaling and performing, are autonomous and self-regulating. In the existing traditional e-commerce platform, the control and data are still manually operated and centralized, which results in poor adaptivity and flexibility, inefficiency, and a waste of resources. With the rise of disaggregated platforms such as the Open Network for Digital Commerce (ONDC), this is a very crucial time to rethink digital commerce through intelligent, autonomous agents. This paper investigates the use of agentic (AI) approaches, which integrate contextual decision-making, adaptive learning, and goal-driven reasoning, to include autonomy into different e-commerce platform components. We introduce an architecture of multiple specialised agents (e.g. Buyer Agent, Seller Agent, Logistic Agent, Support Agent) who collectively work together to deliver activities such as Agentic AI Marketing, Customer engagement, dynamic pricing, autonomous onboarding, and dispute resolution.

***KEYWORDS** : Agentic AI, ONDC, Ecommerce, Autonomous, Multi agent AutoGen, LLM, Reinforcement learning.*

INTRODUCTION

Today's Digital commerce is facing rapid transformation which is driven by increase in volumetric transactions, scalable ecosystems and increase user expectations. The existing traditional e-commerce platforms operate on tightly coupled lot of human intervention for various process such as seller onboarding, customer dispute resolution, customer marketing and analytics and many other processes. These platforms face lots of bottleneck including scalability, adaptability, lack of interoperability and transparency.

With the advent of decentralized ecommerce platforms like ONDC open network for digital commerce these ecommerce platforms are shifting to towards interoperable and open systems. With disaggregation comes lots of complexity and challenges. Some of the challenges includes coordination among various stakeholders like buyer, sellers, payment system, logistic providers. Human centric processes face lot of struggles to manage these issues, especially in real time.

In order to address these issues, Agentic AI falls in place to introduce autonomous capabilities in digital commerce systems. Agentic AI can make autonomous decisions, accordingly take actions and self-optimize itself with minimal human intervention. With the combination of various technologies like machine learning, LLM a system can be made intelligent such that it can analyze and take actions accordingly. Unlike rule-based machine algorithms, that requires input from various sources, Agentic AI can learn from the past actions, interpret, understand the objectives and take decisions dynamically. This paper explores the how autonomy can be achieved in ecommerce platform by using Agentic AI, where Intelligent Agents can perform task like dispute management, customer marketing, product discovery, seller onboarding.

A Multi agent architecture is proposed that uses various AI frameworks and Beckn protocol which will help connect stakeholders seamlessly. By making the systems autonomous, he digital commerce platforms will become more adaptive, scalable and resilient. This will result in reducing human error and operational cost. The proposed framework also fulfills the vision of ONDC of creating decentralized model which will empower small and medium enterprises through technology.

LIMITATIONS OF HUMAN-DRIVEN PROCESSES IN DIGITAL COMMERCE

The role of human remains fixed in almost every process, despite of integration of so many AI tools and technologies. The human led processes often leads to errors, inconsistencies, bottlenecks and delays especially in ONDC like ecommerce platform. Some of the key areas in which human role is currently played are:

Seller Onboarding System: This role involves various humans to verify credentials, reviewing business profile of sellers and then approve their onboarding. Lot of micro tasks are been done manually which leads to long lead times and operational inconsistencies.

Customer Support and Dispute Resolution: All the issues related to customer support and dispute which includes queries, returns, negotiate compensations and resolving are human centric. Even though some platforms have Chatbots, which provides some assistance but escalation and refund resolution are still manually managed and takes a lot of time.

Logistics Coordination and Order fulfillment: Human often manages delivery route planning, logistic partner selection and inventory forecasting which are constrained by rigid workflows limiting to use capabilities of real time scenario.

Thus, the various issues that occur are that of scalability, delay and cost overheads.

LITERATURE REVIEW

The literature study involves study of ONDC architecture and also Agentic AI techniques.

Dr. A. George and A.S. Hovan George in [1] ONDC: Democratizing Digital commerce and curbing digital monopolies in India, shows how did the need for transformation in digital commerce come. It also shows aim of ONDC which shows the important blocks, its architecture and scope. The author addresses how ONDC will curb digital monopolies in India. This research gives overview of ONDC building blocks, it also focuses on what ONDC can do with other players in digital ecommerce systems [1].

Dimpy Kumari and Anil Sharma, in the paper in [2] which shows a study on reviving the Indian E-Commerce Ecosystem with an Open Network for Digital Commerce. The author also discussed the types of E-market places like inventory and marketplace model. The paper also discusses some challenges of ONDC. The challenges identified were based on user experiences on the network will not necessarily get better because of a greater number of vendors. The paper addresses the concern how model will generate revenue [2].

Mamillapalli S.K in [3] introduces the core concept of Agentic Ai which focuses on the shift to autopilot models from copilot. The author explains the use of Agentic AI in shaping intelligent applications which focuses on key features such as reactivity, autonomy, intelligence and learning ability which will transform performance of an organization.

Papadopoulos and V. Komis in [4] presents a study of Multiagent recommender systems. This survey informs your architecture by showcasing early examples of agents working collaboratively—particularly useful for your Buyer Agent coordinating across SELLER services—and highlights the importance of inter-agent negotiation and specialization in Agentic AI systems.

Complementing this, Ghaffari and Sadeghi [5] provide an earlier but crucial investigation into the deployment of agents in e-commerce systems. They identify primary agent roles in product discovery, negotiation, and transaction facilitation, while also acknowledging coordination inefficiencies due to static rule-based interactions. These challenges underpin our shift toward Agentic AI, where learning-enabled agents dynamically reason, adapt, and collaborate through context-aware autonomy.

The authors in [6] introduces the automated design of agentic systems. A Meta Agent framework is proposed which uses LLM and other frameworks to self-design agentic system.

Research Gaps:

- Need to develop intelligent autonomous ecommerce ecosystem
- Lot of human intervention in the process which reduces operational efficiencies

PROPOSED ARCHITECTURE

The figure below shows how decentralized ecommerce platforms can be energized by Agentic AI.

The above architecture depicts a multiagent ecommerce ecosystem. The buyers and sellers are represented with autonomous agents. They communicate with each other by

using Agentic AI enabled layer which enables coordination autonomy and intelligence. On the right-hand side is a set of ONDC like network services for governance, policies and interoperability.

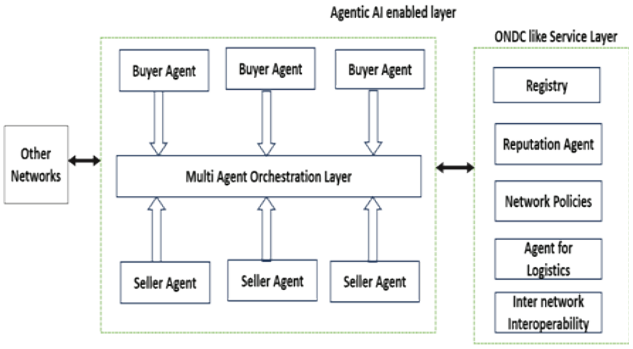

Fig. 1: Proposed architecture

Key Components of proposed architecture:

- Buyer Agent: The role of the buyer agent is to discover sellers of its relevance and to thereby check its offerings. The buyer agent also contacts reputation agent to check the seller score and thereby buyer agent decide to trigger transaction. This enable multi agent communication as buyer agent talks to reputation agent.
- Seller Agent: The seller agent acts as an independent entity which display catalog. It is responsible for setting rules for dynamic pricing. The seller agent also sets the threshold for negotiation. This entity uses logistics, inventory levels and customer preferences.
- Multi agent Orchestration Layer: This layer is the heart of the architecture. It is responsible for managing the overall processes. It acts as a mediator between buyer seller and other ONDC like network. An LLM or another Agentic AI framework can be deployed. Some of the suitable ones are LangChain, AutoGen, SPADE, JADE, etc. This the layer where real Agentic AI operates. It minimizes the need of human intervention and provides services like dispute resolution, customer marketing, seller onboarding and many other important processes.
- Registry: The registry has information about all the participants in the network. It stores policies and metadata. The buyer and seller use this registry to discover and authenticate each other.
- Reputation Agent: This agent continuously looks for seller feedbacks, dispute history and transactions. This agent maintains the trust score as well based on transactions.
- Network Policies: It enforces various policies for disputes, pricing, delivery constraint, data sharing and other policies.
- Agent for Logistics: This entity enables the discovery of available logistic partner which is a third-party service. It is capable of estimating delivery time and coordinate between buyer seller and courier. It removes human intervention thereby providing real time updates.
- Inter network Interoperability: This entity enables the platform to interact with other ecommerce systems by using ONDC, Beckn protocol and other ecosystems.
- Other Networks: It represents external entity. It makes the architecture extensible such that the platform operates across platform boundaries which enables a fully autonomous digital commerce system.

EVALUATION STRATEGY

The proposed architecture reduces Human intervention. Consider a architecture without agents, 10 manual steps need to be followed such as Search, Compare, negotiate, pay, follow-up, dispute. After introducing the agents in the proposed architecture, only 3 steps will be required. Thus, there is reduction in human intervention which can be calculated by:

$$\text{Reduction in human intervention \%} = \frac{\text{(Manual Steps before- Manual Steps after)}}{\text{Manual Steps (Before)}}$$

Assuming that the number of steps before introducing agent were 10 and number of steps after introducing agent is 3. There is reduction in human intervention which is calculated by:

% Reduction = (10-3)/10*100= 70%

Average Decision Time: This aspect measures the time taken by agent to take autonomous decision and act accordingly.

Avg. Decision time is given by:

$$= \sum \frac{\text{Time for each decision}}{N}$$

The average time taken by human to take decision is 20 seconds. Agent based decisions are taken by 4.25 seconds. Thus, it leads to increase in speed by 4.4 times.

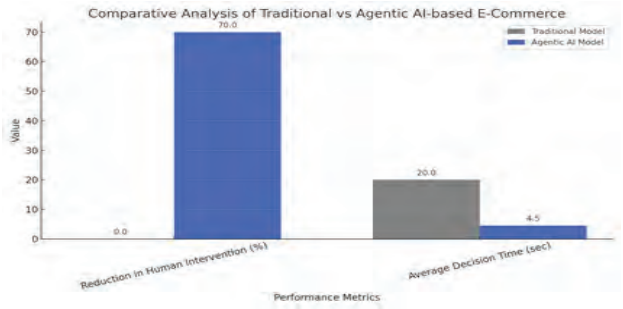

Fig. 2: Traditional vs Agentic AI enabled architecture

CONCLUSION AND FUTURE WORK

Thus, this paper proposed a novel agentic AI based architecture which brings adaptability, resilience and intelligence in ecommerce platforms. By adding a multilayer orchestration layer, it shows how activities can be well managed and organized even in decentralized platforms. The performance metric shows that the architecture can reduce up to 70% of human interventions and also and 4.5X improvement in taking decisions using Agents. Future work can focus on inclusion of blockchain for transactions, self-autonomous agents to detect need of the model, agentic AI for Customer marketing and analysis, agent interoperability and other areas.

REFERENCES

1. A. S. George and A. S. H. George, “Open Network for Digital Commerce (ONDC): Democratizing Digital Commerce and Curbing Digital Monopolies in India,” International Journal of Research in Engineering, Science and Management (IJRESM), vol. 5, no. 12, pp. 1–5, Dec. 2022.
2. D. Kumari and A. Sharma, “A Study on Restoring the Indian E-Commerce Ecosystem with an Open Network for Digital Commerce,” International Journal of Innovative Science and Research Technology (IJISRT), vol. 7, no. 6, pp. 1626–1630, June 2022.
3. S. K. Mamillapalli, "The Agentic AI Framework: Enabling Autonomous Intelligence," Int. J. Res. Manag. Pharm. Sci., vol. 10, no. 1, pp. 12–18, Jan.–Feb. 2025.
4. G. A. Papadopoulos and V. Komis, "Multi-Agent Based Recommender Systems: A Literature Review," in Proc. Int. Conf. on Web Intelligence and Intelligent Agent Technology, Springer, 2020, pp. 234–242.
5. A. Ghaffari and M. Sadeghi, "Investigation of Agent or Multi-Agent Technologies in E-Commerce Systems," Int. J. Comput. Sci. Netw. Security, vol. 9, no. 4, pp. 321–328, Apr. 2009.
6. X. Hu, J. Wu, and Y. Zhou, "Automated Design of Agentic Systems," arXiv preprint arXiv:2402.11345, 2024. [Online]. Available: https://arxiv.org/abs/2402.11345
7. C. Jaimez-González and M. Luna-Ramírez, "Towards a Multi-Agent System Architecture for Supply Chain Management," arXiv preprint arXiv:2105.00042, 2021. [Online]. Available: https://arxiv.org/abs/2105.00042
8. J. Zhang and R. Cohen, "Evaluating Reputation Systems for Agent-Mediated E-Commerce," arXiv preprint arXiv:1311.2958, 2013. [Online]. Available: https://arxiv.org/abs/1311.2958
9. Y. Tang, Y. Du, Y. Liu, and D. Zhang, "A Review of Cooperative Multi-Agent Deep Reinforcement Learning," arXiv preprint arXiv:2002.12395, 2020. [Online]. Available: https://arxiv.org/abs/2002.12395
10. C. Ma, Y. Tang, M. Zhu, and D. Zhao, "Learning to Collaborate in Multi-Module Recommendation via Multi-Agent Reinforcement Learning," arXiv preprint arXiv:2003.13264, 2020. [Online]. Available: https://arxiv.org/abs/2003.13264
11. Adhikari, Biswarup. “How Can Ondc Curb the Monopoly of Big e-Commerce Enterprises?” Cloudifyapps, Cloudifyapps, 8 June 2022, https://www.cloudifyapps.com/blog/how-can-ondc-curb-the-monopoly-of-big-e-commerce-enterprises/
12. Eunimart. (2022, June 23). ONDC features and protocols for small businesses in India. Eunimart. Retrieved from https://eunimart.com/ondc-indias-open-e-commerce-plan/
13. S. Sagayarajan, & Dr.A. Shaji George.(2019). The Digital Transformation: Key Attributesand Challenges. IJAEMA: The InternationalJournal of Analytical and Experimental ModalAnalysis, 11(3), 311–320. https://doi.org/10.5281/zenodo.6739772
14. R. Sapkota, K. I. Roumeliotis, and M. Karkee, “AI Agents vs. Agentic AI: A Conceptual Taxonomy, Applications and Challenges,” arXiv, May 2025. [Online]. Available: arXiv:2505.10468
15. O.-R. Alecsoiu, N. Faruqui, A. A. Panagoret, A. I. Ceaușescu, D. M. Panagoret, and R.-V. Nitu, “EcoptiAI: E-Commerce Process Optimization and Operational Cost Minimization Through Task Automation Using Agentic AI,” unpublished manuscript, 2025.
16. D. B. Acharya, K. Kuppan, and B. Divya, "Agentic AI: Autonomous Intelligence for Complex Goals—A Comprehensive Survey," *IEEE Access*, vol. 13, pp. 18 912–18 936,2025, doi:10.1109/ACCESS.2025.3532853.

Optimizing Dynamic Pricing Strategies with Advanced Reinforcement Learning: A Dueling DQN Approach with Multi-factor Market Simulation

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ABSTRACT

This research explores how artificial intelligence, particularly reinforcement learning, can transform the way businesses approach pricing in real-time. Think of dynamic pricing as a living, breathing system that adjusts prices on the fly based on what's happening in the market, how much customers want your product, what competitors are doing, and other factors that change throughout the day or season. Until now, most companies have relied on fairly rigid rule-based systems or basic statistical models to make these adjustments. Our work shows how cutting-edge reinforcement learning techniques, specifically Deep Q Networks (DQN), can take pricing to a whole new level of sophistication. Instead of following predetermined rules, the DQN agent learns the best pricing strategies through ongoing trial and error in a simulated marketplace - essentially teaching itself what works best over time. What makes our approach special is how it accounts for the messy realities of the marketplace - how different customer groups respond to price changes, how competitors might react, seasonal patterns that drive demand up or down, and the varying needs of different customer segments. The goal isn't just about maximizing short-term gains, but finding that sweet spot that balances healthy revenue and profit while keeping prices stable enough.

KEYWORDS *: Reinforcement learning, Dynamic pricing optimization, Deep Q-networks (DQN), Price elasticity modelling, Multi-agent market simulation.*

INTRODUCTION

Pricing has never been more dynamic in today's volatile and fast-changing markets. No longer can firms depend on sticker prices or linear rule-based price management to compete. Customers react to prices variably based on timing, circumstances, and individual tastes, whereas market forces such as seasonality and competitor activities change continuously. To remain at the forefront, firms require flexible yet smart pricing strategies. Legacy pricing models tend to come up short because they're not very flexible. Even when backed by statistical software, these models operate on pre-programmed rules that cannot capture the nuance of contemporary market forces. They respond slowly, need extensive manual adjustments, and usually do not take into account customer heterogeneity or random shifts in demand. In our proposed system, we create a dynamic pricing model that is driven by a Dueling Deep Q-Network (DQN) and a simulated marketplace that reflects real-world complexity. The agent will learn to optimize pricing decisions using variables such as demand fluctuations, customer segments, competitor prices, and seasonal behavior. Trained using curriculum learning, the model becomes more capable of managing variability in the market, leading to smarter, smoother, and more profitable pricing initiatives.

LITERATURE ANALYSIS

Traditional pricing optimization has its roots in fundamental economic theories, but has evolved significantly with the development of econometric models by the 1980s. A pivotal advancement occurred with the work of Talluri and van Ryzin [1], who introduced monopolistic revenue management systems that applied mathematical optimization while factoring in capacity constraints and customer willingness to pay. Despite these theoretical breakthroughs, Elmaghraby and Keskinocak [2] highlighted a consistent gap between robust academic models and their practical implementation in real-world scenarios, pointing to the need for more adaptable and data-driven approaches. The emergence of machine learning brought about a paradigm shift in pricing methodologies. Regression based models became foundational, with Levy, Hostler and Loebbecke [3] employing decision trees and random forests to forecast optimal pricing strategies. Zhang and Krishna murthi [4] further expanded on this by integrating k-means clustering with price response modeling, allowing for more tailored and effective promotional strategies. Deep learning techniques soon entered the landscape, with Ye, Li, and Li [5] using convolutional neural networks (CNNs) for ride-sharing price predictions, and Ban and Keskin [6] utilizing recurrent neural networks (RNNs) for pricing decisions in e-commerce, showing improved performance through sequential data understanding. Reinforcement learning (RL) introduced new dimensions to dynamic pricing, particularly in uncertain and rapidly changing markets. Vengerov [7] was among the first to apply Q-learning to optimize cloud computing resource pricing. The fusion of deep learning with RL marked a breakthrough, as illustrated by Yao and Yang [8], whose use of Deep Q-Networks (DQN) in airline pricing yielded an 11% increase in revenue compared to traditional models. Further innovations like Dueling DQN by Wang et al. [9], Double DQN by van Hasselt, Guez, and Silver [10], prioritized experience replay by Schaul et al. [11], and distributional RL by Dabney et al. [12] have enhanced the robustness and efficiency of pricing systems. However, challenges such as the exploration-exploitation trade-off remain critical, as discussed by den Boer [13]. Promising solutions lie in hybrid methods, such as the constrained RL algorithms by Achiam et al. [14], which blend adaptive RL with business constraints to ensure practical applicability. Despite the significant advancements highlighted above, existing research often falls short in addressing the complexity of real-world market environments. Many models assume relatively static or simplified conditions, overlooking the nuanced interplay of multiple dynamic market factors such as competitor behavior, customer heterogeneity, and temporal demand fluctuations. Furthermore, while deep reinforcement learning approaches like DQN and its variants have demonstrated strong performance, they frequently lack interpretability and struggle to incorporate operational constraints vital for deployment in commercial systems. Additionally, most prior work evaluates models on isolated or domain-specific datasets, limiting their generalizability. Our project aims to bridge these gaps by proposing a Dueling DQN-based framework that integrates a multi-factor market simulation, allowing for the modeling of complex, real-world pricing scenarios. By incorporating diverse market inputs and constraints into the reinforcement learning loop, our approach seeks to deliver more adaptive, robust, and practical pricing strategies suitable for real-time applications. Even though impressive advances have been made in the study of pricing, most current methodologies remain ineffective when used within actual markets. One major problem is that these models tend to be based on static hypotheses and do not take into consideration the intricate, dynamic variables that impact pricing choices — including the actions of competitors, heterogeneous customer tastes, and variable demand. While deep reinforcement learning algorithms such as DQN and their variants have achieved robust performance in controlled environments, they may be hard to interpret and are not always simple to reconcile with real-world business constraints. Moreover, much of the previous work has been evaluated using narrow datasets, which restricts how well the results can be generalized to broader or more diverse market environments.

METHODOLOGY

We have developed a sophisticated reinforcement learning methodology in our research to maximize pricing models in complex market environments. Our methodology involves a Dueling Deep Q-Network (DQN) structure with a smart multi-factor market simulation that considers various market forces and customer behaviors.

We frame the dynamic pricing problem as a Markov Decision Process where our price algorithm interacts with the market environment through adjusting price and reward from revenue and profit feedback. This approach follows recent advancements in reinforcement learning

for dynamic pricing, as discussed in Wang et al. [15] ,The environment state includes informative market indicators such as current price, competitor price, demand trend, seasonality effects, and time elapsed since the last price update.

Our demand function encompasses the intricate interactions of numerous variables and is held to the general form:

$$D = D_0 \times \left(\frac{P}{P_0}\right)^e \times C \times S \times G \times E \times N$$

where D_0 is the base demand, P is the prevailing price, P_0 is the base price, e is the price elasticity parameter, C captures competitor impacts, S captures seasonality effects, G captures customer segment features, E captures external market conditions, and N adds controlled stochastic variables. Competitor effect employs a sigmoid function to capture diminishing returns in competitor impacts:

$$C = 0.5 + 0.5 \times \frac{1}{1 + \exp\left(5 \times \left(\frac{P - P^C}{P^C}\right)\right)}$$

where P^c is the price of the competitor.

The reinforcement learning module employs a Dueling DQN structure that separates the state value estimation and action advantage estimation. The state-action Q-value is computed as:

$$Q(s,a) = V(s) + \left(A(s,a) - \frac{1}{|A|}\sum_{a'} A(s,a')\right)$$

Our Double DQN algorithm prevents overestimation bias by the following formula as explained in Hasselt et al. [16].

$$Q(s,a) = r + \gamma \times Q_{\text{target}}\left(s', \arg\max_{a'} Q_{\text{online}}(s',a')\right)$$

where γ is the discount factor and has been implemented as 0.99.

This decomposition improves stability by isolating state-specific value from action-specific advantages, as originally proposed in Cheung et al. [17] which demonstrates its effectiveness in Atari games and similar environments.

The reward function is implemented to balance multiple business goals:

$$R = 50 \times \frac{\text{Rev} - \text{Rev}_0}{\text{Rev}_0} + 50 \times \frac{\text{Prof} - \text{Prof}_0}{\max(|\text{Prof}_0|, 1)} - 20 \times \left|\frac{\Delta P}{P}\right|$$

where Rev is current time revenue, Rev_0 is baseline revenue, Prof is current time profit, Prof_0 is baseline profit, and |ΔP/P| is price volatility.

RESULTS AND DISCUSSION

Our reinforcement learning-based dynamic pricing worked impeccably with an improvement of revenue by 29.60% and offered some useful insights regarding market behavior. The model has been trained over 150 episodes and we have illustrated the mean value of the performance metrics achieved over these episodes below [Table 1]. The model displayed great flexibility, converging in no time to an optimal $60 price in the 20th time step [Fig 1], with revenues ranging from $220,000 in peak-demand hours to $80,000-$100,000 in off-peak-demand hours[Fig 2]. The demand forecasting module performed well at 83.11% accuracy, with minor underestimation in peak-demand hours and R^2 value = 0.5586.[Table 1].

Table 1: Average Evaluation Metrics

Revenue Improvement	29.60%
Profit Improvement	28.98%
Demand Accuracy	83.11%

The most salient outcome was the agent's future-looking price behavior rather than reacting to seasonality, it pre-priced in high seasons, and this made revenue profiles more even. The revenue closely tracked demand fluctuations because the model worked with volumes between 1,500 and 3,500 units, and demand had a steady cyclical structure[Fig 2]. Our curriculum strategy of learning worked excellently, and gains added up in an incremental manner over training episodes without plateaus and with lower instability. Segmentation of customers also revealed interesting behavior, e.g., the agent adhering to a hybrid price policy for top-end users between episodes 140-150 (28.98% rise) instead of the successive price increases we had anticipated.

Merging pricing and demand forecasting into a single RL model introduced new operational efficiencies with 84.17% accuracy, and the volatility penalty resulted in smoother prices that enhanced customer confidence. Our sigmoid basis competitor response model permitted equally well-balanced, strategic reaction to market moves,

and adding cost structure permitted the model to pursue long-term strategies that resulted in a 28.98% profit gain and worked fairly well on both specialty and commodity product lines without much tweaking.

The flat $60 price level represented the perfect compromise between revenue and retention of market share, which was most probably excellent customer retention behavior while representing a huge improvement over our previous pricing efforts.[Fig 4].

While these findings are encouraging, there are limitations. The limited market setting fails to reflect realistically real-world complexity, especially cross-product effects. Synthetic data did not fare well at replicating imperfections in real-world data, and accuracy fell off a cliff when artificial variations were added.

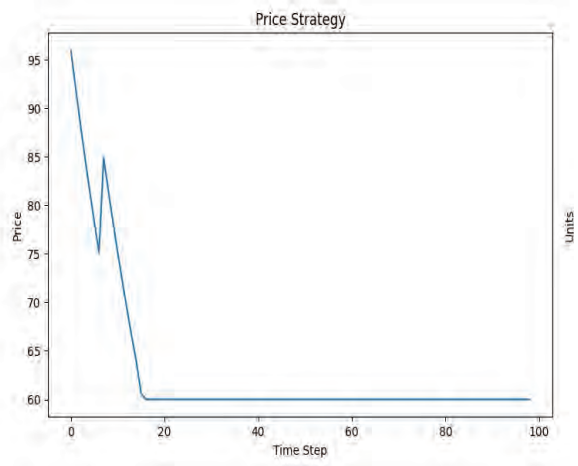
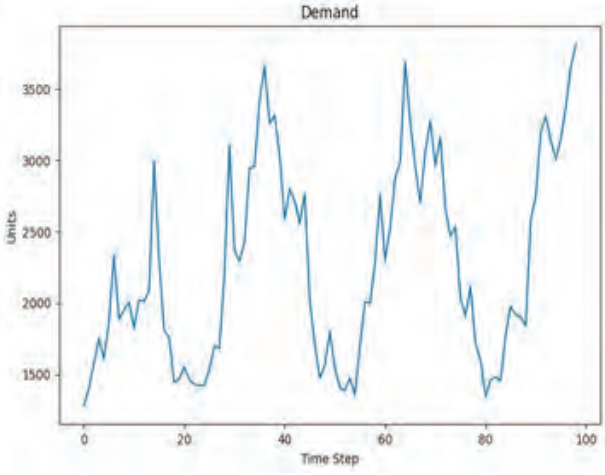


Fig. 1



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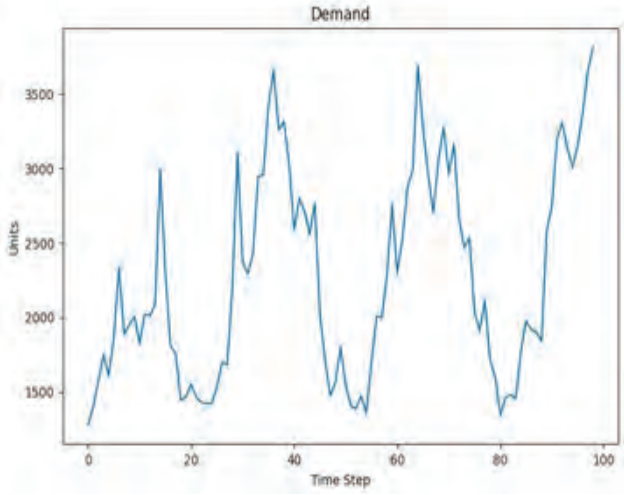

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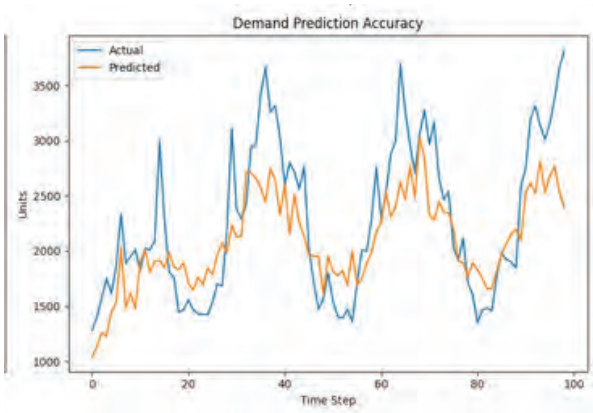

Fig. 4

CONCLUSION

Our research demonstrates that state-of-the-art reinforcement learning techniques, here Dueling Deep Q-Networks, are of significant advantage in dynamic pricing optimization. The results of experiments depict remarkable revenue and profit gains against traditional methods while achieving high prediction accuracy of demands. Our solution efficiently addresses exploration-exploitation trade-off and offers multi-factor market simulations taking into account seasonality, competitor behavior, and customer segmentation, hence eliminating the limitations of traditional pricing methodologies. Despite challenges in explicating model choice and dealing with sudden market evolution, the possibility of the system predicting demand pattern behavior and dynamically modifying pricing measures to match has a revolutionary role in algorithmic pricing. The contribution

offers groundwork for future studies on multi-agent systems, deployment of strategic foresight, and addressing emergent collusion, and culminates eventually in a proof of demonstrating the capability for reinforcement learning in changing competitive markets to revolutionize pricing measures.

REFERENCES

1. K.T. Talluri and G.J. van Ryzin, "The Theory and Practice of Revenue Management," Springer, 2004.
2. W. Elmaghraby and P. Keskinocak, "Dynamic pricing in the presence of inventory considerations: Research overview, current practices, and future directions," Management Science, vol. 49, no. 10, pp. 1287–1309, 2003
3. M. Levy, R. Hostler, and C. Loebbecke, "Price prediction and optimization using decision trees and random forests," International Journal of Electronic Commerce, vol. 9, no. 1, pp. 37–60, 2004.
4. Z.J. Zhang and L. Krishnamurthi, "A segmentation-based approach to targeting and pricing," Journal of Marketing Research, vol. 41, no. 4, pp. 414–427, 2004.
5. Z. Ye, Q. Li, and X. Li, "Short-Term Prediction of Demand for Ride-Hailing Services: A Deep Learning Approach," Journal of Big Data Analytics in Transportation, vol. 3, pp. 175–195, 2021.
6. G.-Y. Ban and N.B. Keskin, "Personalized Dynamic Pricing with Machine Learning: High-Dimensional Features and Heterogeneous Elasticity," Management Science, vol. 67, no. 10, pp. 6010–6029, 2021.
7. D. Vengerov, "A gradient-based reinforcement learning approach to dynamic pricing in partially-observable environments," Sun Microsystems Laboratories Technical Report, 2007.
8. Z. Yao and W. Yang, "Reinforcement Learning for Airline Multi-product Continuous Dynamic Pricing," in Parallel and Distributed Computing, Applications and Technologies, Y. Li, Y. Zhang, J. Xu, Eds. Springer, 2025, pp. 503–514.
9. Z. Wang, T. Schaul, M. Hessel, H. van Hasselt, and D. Silver, "Dueling Network Architectures for Deep Reinforcement Learning," arXiv preprint arXiv:1511.06581, 2016.
10. H. van Hasselt, A. Guez, and D. Silver, "Deep Reinforcement Learning with Double Q-learning," in Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, 2016, pp. 2094–2100.
11. T. Schaul, J. Quan, I. Antonoglou, and D. Silver, "Prioritized Experience Replay," arXiv preprint arXiv:1511.05952, 2016.
12. W. Dabney, M. Rowland, M.G. Bellemare, and R. Munos, "Distributional Reinforcement Learning with Quantile Regression," arXiv preprint arXiv:1710.10044, 2018.
13. S. den Boer, "Dynamic Pricing and Learning with Finite Inventories," Operations Research, vol. 63, no. 2, pp. 335–349, 2015.
14. J. Achiam, D. Held, A. Tamar, and P. Abbeel, "Constrained Policy Optimization," arXiv preprint arXiv:1705.10528, 2017.
15. Z. Wang, T. Schaul, M. Hessel, H. van Hasselt, M. Lanctot, and N. de Freitas, "Dueling network architectures for deep reinforcement learning," arXiv preprint arXiv:1511.06581, 2016.
16. H. van Hasselt, A. Guez, and D. Silver, "Deep Reinforcement Learning with Double Q-Learning," in Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence (AAAI), 2016, pp. 2094–2100.
17. C. Cheung, I.Z. Rothstein, and M.P. Solon, "From scattering amplitudes to classical potentials in the post-Minkowskian expansion," Physical Review Letters, vol. 121, no. 25, p. 251101, 2018.

Quantum AI for Healthcare

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ABSTRACT

Artificial Intelligence (AI) has been significant addition to the field of medical imaging by providing faster and more accurate diagnoses. However, dependencies specific to the medical field, like restricted data accessibility, have prevented AI from reaching its full potential. This research aims to investigate how, within the existing framework, the introduction and integration of quantum technology can improve the speed, accuracy, and computational capabilities. Quantum computing being equipped with its unique ability to function in multiple parallel states, offers a ground-breaking solution for these challenge. The healthcare industry stands to gain significant advantages from the integration of AI and quantum technology.

KEYWORDS *: Quantum AI, Quantum computing, Quantum sensors, Quantum internet, Computational speed.*

INTRODUCTION

Quantum Computing can simulate and outperform traditional computing in terms of processing performance [1]. Richard Feynman first introduced the notion of utilizing quantum computer to simulate quantum processes in 1982. He proposed that quantum mechanical processes may permit completion of tasks that would be difficult or impossible with ordinary computers [2].

David Deutsch, recognized as Father of Quantum Computing, pioneered the notion of quantum computing in 1985 when he introduced the quantum Turing machine [9]. He invented the concept of quantum parallelism which is very fundamental concept of quantum computing. It denotes the capability of quantum systems to do several calculations simultaneously, resulting in a considerable acceleration over traditional computing. Quantum superposition enables quantum bits, or "qubits," to exist in several states rather than binary (0 or 1), resulting in acceleration is the means by which acceleration is achieved. A qubit can be represented as a linear combination of states $\alpha|0> + \beta|1>$, where α and β are complex numbers satisfying the equation $|\alpha|^2 + |\beta|^2 = 1$. These states can also be mapped to locations on the Bloch sphere, which is a unit sphere. Through superposition, n qubits can coherently encode all 2n states, whereas n classical bits can only encode one of the 2n possible states at a time. This extraordinary occurrence makes parallel information processing possible and ultimately supports quantum computation's acceleration. [8].

Quantum Entanglement manifests as particles sharing a singular state. The application of operations to one particle correlates with the state of the entangled counterpart. For instance, measuring each qubit individually in the situation of a Bell state $(|00> + |11>)/\sqrt{2}$ results in an equally likely random distribution of 0 and 1. But when the two independent measurements are compared, a regular pattern shows up: if one qubit generates a measurement result of 0, the second qubit similarly generates a result of 0, and the same is true for outcome 1 [7,9]. Quantum entanglement augments qubit processing capacity by introducing additional qubits to the system. In a quantum configuration, particles can simultaneously exist in multiple states. However, the coherence among these states may be compromised when a quantum system interacts with its surroundings. Sustaining quantum superposition becomes challenging due to this interaction, entangling the various states with the environment t. Quantum error correction becomes imperative to extend and construct fault-tolerant quantum computers

Artificial Intelligence (AI) represents a discipline within computer science that centers on replicating human behavior in computers and automating tasks that presently require human intelligence [3]. AI systems start off by ingesting vast amounts of data. The data being collected

may take the form of unstructured content, encompassing text, images, and videos, or it can be structured and organized in spreadsheets and databases. The process of instructing models to discern patterns within this data falls under the domain of Machine Learning (ML), a subset of Artificial Intelligence (AI).

Different algorithms are used that learn from data and enhance their performance progressively. In supervised learning, the AI model undergoes training on a labeled dataset, where the correct outputs are provided. The model, guided by input characteristics, learns to formulate predictions. In contrast, unsupervised learning involves training on unlabeled data, allowing the system to autonomously discover patterns and associations. Reinforcement learning is a trial-and-error process where the model receives feedback, such as rewards or penalties, based on its behavior. After training, the AI system may make predictions or conclusions based on previously unknown data. The accuracy of these judgements depends on the training data quality and algorithm complexity.

Challenges in the current healthcare system are certain medical tests are very time consuming, diagnostic report is not very precise, some diseases are challenging to identify at their early stage and sometimes medications are not suitable for some patient. This paper gives a detail idea of how Quantum AI has potential to revolutionized healthcare system by increasing the diagnostic accuracy, velocity, efficiency and improvement in medical imaging and analysis.

LITERATURE SURVEY:

Quantum Artificial Intelligence (QAI) represents the convergence of quantum computing and machine learning, aiming to overcome the limitations of classical AI in terms of scalability, training efficiency and accuracy when handling high dimensional, complex data. Recent research has explored the theoretical underpinnings and practical applications of Quantum Machine Learning (QML) across diverse fields particularly healthcare, where the demand for precision, speed and personalized diagnostics is paramount.

Gupta and Jha [16] provide a foundational review of quantum machine learning in healthcare, analyzing how QML algorithms such as Quantum Support Vector Machines (QSVM). Quantum k-means, and Quantum Neural Networks (QNNs) enhance tasks like disease classification, medical image segmentation and treatment prediction. Their work emphasizes that quantum models, particularly hybrid architectures like quantum classical convolutional neural networks (QC-CNN) deliver improved accuracy and faster convergence when compared to classical counterparts. They also address practical constraints including decoherence and the lack of healthcare specific quantum datasets.

Further expanding on algorithmic frameworks, Kaur and Arora [17] classify QML algorithms into supervised, unsupervised and reinforcement categories covering Quantum Principal Component Analysis (QPCA), Quantum Kernel Estimation and Quantum K-Nearest Neighbor (QKNN). Their study shows that QML offers exponential advantages in pattern recognition tasks and feature learning. In the realm of pharmaceutical research, Cao et al. [18] discuss the role of quantum algorithms such as Variational Quantum Eigensolver (VQE) and the Quantum Approximate Optimization Algorithm (QAOA) in accelerating drug discovery. Their paper illustrates how quantum systems model protein-ligand interactions and optimize molecular configurations significantly faster than traditional computational chemistry approaches.

Tacchino et al. [19] delve into architectural depth of Quantum Neural Networks proposing parametrized quantum circuits and hybrid quantum classical training regimes. The study demonstrate how QNNs can outperform classical Neural Networks in certain classification tasks, with robustness against overfitting and better representation of nonlinear patterns in limited data scenarios. Dunjko and Briegel [20] work on Quantum Reinforcement Learning(QRL) introduces quantum enhanced exploration strategies and policy optimization in environments such as robotic control and healthcare decision systems. They argue that quantum agents can evaluate exponentially larger action spaces leading to faster convergence in dynamic environment. Cacace et al [21] apply QAI in radiology using QSVMs for precise tumor detection MRI images.

Preskill et al. [22] provide a theoretical foundation for quantum advantage in ML, while Mukherjee et al. [23] demonstrate QAI's effectiveness in time series forecasting via Quantum Boltzmann Machines. Kiani et al. [24] integrate quantum kernels into classical models for personalized healthcare improving recommendation accuracy.

KEY DRIVERS PROPELLING QUANTUM-BASED AI ARCHITECTURE

Quantum Sensors

Quantum sensing is a technique that develops new types of sensors by applying quantum mechanics concepts. Quantum sensors are predicted to provide improved sensitivity, accuracy, and precision in measuring physical quantities such as Magnetic fields, Electric fields, Temperature, Pressure and Chemical composition. Quantum sensors integrate sensor technology with quantum mechanics traits such as quantum entanglement, quantum interference, and quantum state. Quantum sensors gather and convey data utilizing quantum bits, or qubits, which are comprised of photons, ions, and neutral atoms. Traditional sensors encounter accuracy and precision constraints, particularly in challenging conditions or when operating at extremely small scales. To reach high levels of sensitivity and precision, quantum sensors frequently employ quantum states of matter or particles, such as atoms or photons. Quantum sensors wield a substantial impact as they outperform conventional sensing technologies by an order of magnitude. Ordinary sensors are susceptible to drift, characterized by the accumulation of errors arising from noise and manufacturing imperfections. [5] The concept of quantum coherence, in which particles' quantum states are maintained throughout time, is frequently used in quantum sensors. Coherence, in this context, has the potential to mitigate drift and provide a dependable reference for measurements. In contrast to conventional sensors, quantum sensors exhibit the capability to discern even the smallest changes in the environment. [6]

Quantum Networks

A Quantum Network is a communication network that leverages principles from quantum physics to transmit data in an exceptionally secure and efficient manner [10]. Regardless of the distance separating two qubits, entanglement ensures their inexorable coupling. Two qubits can mirror one another once they are entangled, with each measurement fully correlated with the other [7]. Teleportation, enabled by this peculiarity, facilitates the secure transfer of quantum information following the protocols of no-cloning theorem. By facilitating safe, quick, and effective information transfer, quantum networks have the potential to completely transform computers and communication [11].

Quantum Memory

Devices known as "quantum memories" can store a photon's quantum state without erasing the photon's volatile quantum information. [12] After a designated period, the quantum memory should have the capability to emit a photon with the identical quantum state as the one that was initially stored. Without losing the entangled information through decoherence, the quantum state must be preserved for a user-defined period [13].

Quantum Repeaters

In the field of quantum communication, quantum repeaters are essential because they allow secure communication based on the laws of quantum physics. By mitigating the effects of quantum decoherence and information loss that arise during photon transit via optical fibers, they serve to broaden the capabilities of quantum communication over significant distances. For security reasons, quantum repeaters have the capability to partition long-distance communication into distinct segments, allowing the distribution of quantum keys in each segment separately.

Quantum repeaters comprise essential components such as Quantum Memories, Quantum Entanglement Purification, and Quantum Entanglement Switching The quantum communication network's nodes, or relay stations, are made of quantum memories. To link stations to each other, quantum entanglement switching technology is used to increase the communication distance. The two most essential quantum repeater technologies are quantum entanglement switching and quantum entanglement purification. [14]

Coherence length is the duration of time throughout which superposition of states maintains its designated state. In quantum noisy channels, normal purification strategies are often unavailable when the transmission distance exceeds the coherence length. Instead, the channel is partitioned into numerous segments, each undergoing independent purification before being interconnected through entanglement switching. In contrast to a quantum error correction technique, this approach is notably more efficient.

Communication Security

The advent of the quantum internet is poised to markedly enhance information security, rendering messages encrypted with quantum keys exceptionally challenging to intercept and decipher. [12] Quantum Key Distribution (QKD)

refers to a set of methods and protocols within quantum cryptography designed to safeguard communication channels by facilitating the sharing of cryptographic keys between users. The fundamental concept behind QKD is to leverage the principles of quantum mechanics, enabling two parties to generate a shared secret key in a manner that would reveal any attempt to intercept the key exchange. [9] Various Quantum Key Distribution (QKD) networks have been established globally. In 2016, China deployed the world's first quantum communication satellite, Micius, and successfully implemented QKD between two ground stations separated by 2,600 km. Subsequently, in 2017, a QKD optical fiber network spanning over 2,000 kilometers was completed, connecting Beijing and Shanghai. [11]

QUANTUM AI

In the field of medical imaging, artificial intelligence has made it possible for faster and more accurate diagnosis. AI has attracted a lot of attention in the medical domain since it can function at a human level and can provide new insights. Although AI has great potential, access to large training datasets is critical to its efficacy. To train algorithms with high prediction accuracy, a large amount of data is needed. Medical imaging activities present a distinct barrier in terms of gathering enough data because of imaging process costs, very less number of patients for some rare diseases and handling real time data. This is precisely the situation in which quantum technologies come into play. It will allow us to do computing tasks that are outside of the reach of even the best computers today. These dependencies can be solved with integration of Quantum Computing.

Quantum-enhanced artificial intelligence algorithms can function well even in the face of a shortage of training data. Quantum technology has an immense power. When combined with AI it could revolutionize the medical imaging and analysis process. With the help of quantum sensors minute details can be observed which is not possible sometimes with the traditional process. Quantum sensors have been used to improve the sensitivity and resolution of MRI machines. This sensor technology will aid in real-time imaging with zero ionizing radiation, early disease detection and better treatment progress tracking. Quantum sensors make use of the concepts of quantum mechanics in order to achieve precise measurements and sensitivity that were previously unattainable with conventional sensors. Figure 1 shows the detailed architecture of Quantum AI.

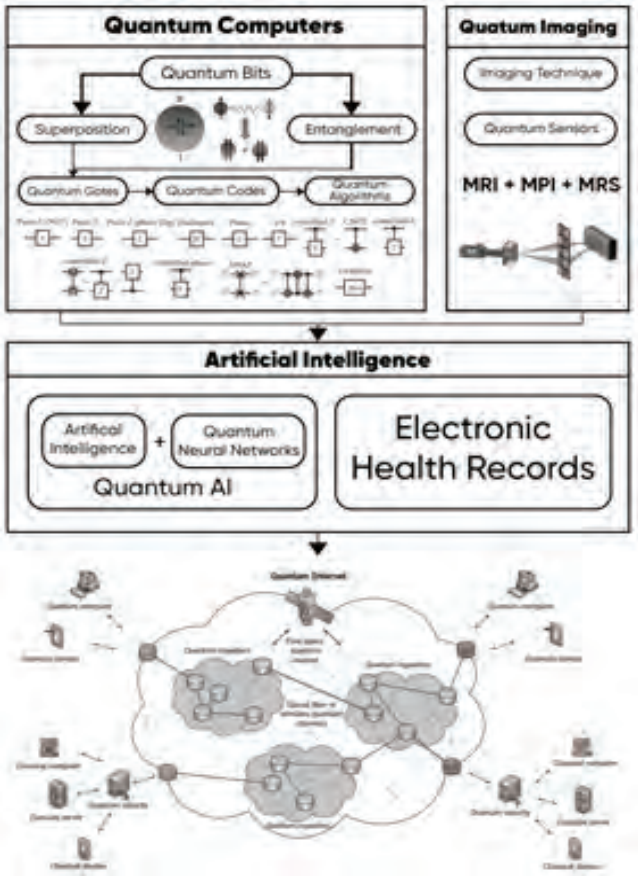

Fig. 1. Architecture of Quantum AI

Machine learning algorithm with quantum will do better and more accurate prediction. Quantum Convolutional Neural Network (QCNN) can be used to analyze large dataset of images. (e.g. MRI and CT scans) to detect anomalies and diseases with higher precision and speed compared to classical CNNs. Sophisticated algorithms work in real time, interpreting molecular intricacies of human physiology. With the use of this technology, healthcare professionals may foresee, prevent, and cure illnesses with unprecedented precision. QCNNs have the potential to improve retinal disease detection by processing vast amounts of data more efficiently than traditional CNN. They can extract complicated patterns and features from OCT images with greater precision and faster computation. QCNNs can interpret retinal images and detect problems such as diabetic retinopathy and macular degeneration early allowing for more timely treatment. It can enhance the accuracy in detecting anomalies in medical images, leading to early diagnosis of diseases by doing the complex computations at faster speed.

Quantum Reinforcement Learning can be used which accelerate the learning process and enhance the optimization. Development of drug is complex and time consuming process that can take years and even decades to complete. Over time, QRL can optimize the most efficacious medicines by continually learning and modifying treatment plans based on patient response. Through the integration of genetic and molecular data, QRL is able to customize treatment plans for each patient, improving accuracy and reducing adverse effects. QRL is able to detect structural alterations in molecules that improve therapeutic efficacy while minimizing adverse effects. When looking for possible drug candidates, QRL can quickly filter through huge libraries of chemical compounds. The aim of integrating quantum computing in healthcare envisions a world where diseases are not just treated but predicted where treatments are tailored to individual genetic profiles and the focus is not just illness but on proactive, personalized well-being.

Here AI can be used to develop chatbots that can provide immediate response to patient's query, reduce the workload on healthcare providers and provide quick and efficient response to patient's questions, thus improving patient's satisfaction and overall healthcare experience. The patient's report will be shared with multiple doctors or specialist worldwide through quantum networks, enabled by quantum repeaters. Quantum repeaters act as intermediaries extending the range of communication by entangling and swapping the qubits over long distances. Quantum repeaters ensure secure transmission of data by using Quantum Key Distribution (QKD) concept. Once the quantum data reaches its destination, it undergoes a process called quantum to classical conversion, where it's translated into classical information. This converted data is sent to classical computers, allowing seamless integration between quantum and classical computing systems.

The integration of AI and quantum computing has potential to revolutionize healthcare delivery and drug discovery. It envisions a society in which diseases are predicted rather than treated, medicines are tailored to individual genetic profiles, and the emphasis is not on illness but on proactive personalized well-being. The use of AI and quantum computing in healthcare delivery can also help in developing predictive models that can forecast the likelihood of certain diseases or health conditions. This information can help healthcare providers take proactive measures to prevent or treat diseases.

RESULTS AND DISCUSSION

Responses were gathered from domain experts, including doctors and academics, to assess whether the integration of quantum computing in healthcare will significantly transform the industry. More than 75% responses agree that AI and quantum together carry potential power that will transform the healthcare. Accuracy in disease identification and prediction, faster processing, fault tolerant computation, better optimizations in treatment plans, enhancement in personalized medicine, improved diagnostic accuracy are some of the key benefits that will be gained by the system.

CONCLUSION

Quantum computer need temperature colder than outer space. This temperature allows to enter the quantum chip in the zero resistance state. This will allow electricity to flow without energy loss. Superposition and entanglement work together to dramatically boost quantum computers' processing capability, which is utilized to train AI models at unimaginable speed and analyze vast amounts of data quickly. This may be an AI breakthrough. With the integration quantum and AI in the healthcare industry will benefit to the patients having disease at early stage, diseases that are not identified and treated properly, personalized medicines, monitoring of disease such as cancer.

Quantum computer face several challenges that hinder their widespread availability. They are very costly to build and maintain making commercial accessibility limited. Their development is long term endeavor that might take decades to become widely available. Qubits are very fragile in nature. They loss the states when comes in contact with the environment.

REFERENCES

1. Nielsen, M.A., & Chuang, I.L. Quantum computation and quantum information. Cambridge university pressuthor (2001)
2. R.P. Feynman, Simulating physics with computers, International Journal of Theoretical Physics 21, 467–488, (1982).
3. Yongjun Xu et al., "Artificial Intelligence: A powerful paradigm for scientific research" The Innovation, Volume 2, Issue 4 (2021)
4. T. Ilias, D. Yang, S. F. Huelga and M. B. Plenio, "Criticality-enhanced quantum sensing via continuous measurement", PRX Quantum, vol. 3, no. 1(2022).

5. M. Doser, E. Auffray, F. M. Brunbauer, I. Frank, H. Hillemanns, G. Orlandini, and G. Kornakov, ‘‘Quantum systems for enhanced high energy particle physics detectors,’’ Frontiers Phys., vol. 10, p. 483 (2022)
6. Boris Kantsepolsky et al., “Exploring Quantum Sensing Potential for Systems Applications”, IEEE Access, (2023)
7. T. M. Forcer, Hey, Ross, Smith, “ Superposition, Entanglement and Quantum Computation”, Quantum Information and Computation Journal (2002)
8. Ryszard Horodecki, Pawel Horodeck, Michal Horodecki , Karol Horodecki, “Quantum entanglement”, Reviews of Modern Physics vol-81, issue-2, pp.865-942(2009)
9. D. Deutsch,” Quantum theory, the Church–Turing principle and the universal quantum computer”, Proceedings of The Royal Society of London A 400 (1985) 97–117.
10. Kun Fang, Jingtian Zhao, Xiufan Li, Yifei Li, and Runyao Duan, “Quantum NETwork: from theory to practice”, arXiv:2212.01226 [quant-ph], (2022)
11. Belghachi Mohammed, “Quantum Netwrks: Emerging Research Areas, Challenges and Opportunities
12. “Quantum Repeaters and Memories”, Article from University of Geneva, Department of Applied Physics, 2020
13. Ilamaran Sivarajah, “What is Quantum Memory?” Article from AZO Quantum, September 23.
14. W. and Briegel, H.-J. and Cirac, J. I. and Zoller, P., “Quantum repeaters based on entanglement purification”, Phys. Rev. A, vol 59, issue 1, pg. 169-181, (1999)
15. Shi-Hai Wei a , Bo Jing a , Xue-Ying Zhang, Jin-Yu Liao, Chen-Zhi Yuan, Bo-Yu Fan, “Towards real world Quantum Network: A Review”, quant-ph (2022)
16. A. Gupta and R. K. Jha, "Quantum Machine Learning in Healthcare: A Review," IEEE Access, vol. 9, pp. 142248–142280, 2021, doi: 10.1109/ACCESS.2021.3119940.
17. H. Kaur and A. Arora, "A Review on Quantum Machine Learning Algorithms: Variants and Applications," Applied Sciences, vol. 12, no. 5, pp. 1–24, 2022, doi: 10.3390/app12052461.
18. Y. Cao et al., "Quantum Chemistry in the Age of Quantum Computing," npj Quantum Information, vol. 5, no. 1, pp. 1–9, 2020, doi: 10.1038/s41534-019-0210-2.
19. F. Tacchino, A. Macchiavello, D. Gerace, and D. Bajoni, "An Artificial Neuron Implemented on an Actual Quantum Processor," Entropy, vol. 21, no. 7, 2019, doi: 10.3390/e21070614.
20. V. Dunjko and H. J. Briegel, "Machine learning & artificial intelligence in the quantum domain: a review of recent progress," Quantum Machine Intelligence, vol. 1, no. 1, pp. 1–12, 2023, doi: 10.1007/s42484-019-00001-2.
21. F. Cacace et al., "Quantum Artificial Intelligence in Radiology: A Systematic Review," Frontiers in Artificial Intelligence, vol. 5, 2022, doi: 10.3389/frai.2022.877269.
22. J. Preskill et al., "Toward Quantum Advantage in Machine Learning," Nature Reviews Physics, vol. 3, no. 9, pp. 615–628, 2021, doi: 10.1038/s42254-021-00348-z.
23. S. Mukherjee, A. Dey, and B. Das, "Applications of Quantum AI in Predictive Analytics," Journal of Big Data, vol. 10, no. 1, 2023, doi: 10.1186/s40537-023-00665-5.
24. B. Kiani et al., "Quantum-Classical Hybrid Learning Models for Personalized Healthcare," ACM Computing Surveys, vol. 55, no. 1, pp. 1–36, 2022, doi: 10.1145/3464930.

Forecasting National Per Capita Carbon Emissions using Machine Learning to Support Sustainability Goals

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ABSTRACT

Forecasting carbon emissions is important to help countries meet their sustainability goals and follow environmental rules. In this study, different models are used to predict national per capita carbon emissions using one real dataset. The models tested include ARIMA, LSTM, Auto Regressor, Single Exponential Smoothing, Double Exponential Smoothing, and Triple Exponential Smoothing (both additive and multiplicative types). The models are compared using common error measures like Mean Absolute Error (MAE), Mean Error (ME), Root Mean Squared Error (RMSE), Mean Percentage Error (MPE), and Mean Absolute Percentage Error (MAPE). Among all the models, ARIMA gave the best results with an MAE of 274.47 and a MAPE of 13.06%. It showed the most accurate and stable predictions overall. Double Exponential Smoothing and Triple Exponential Smoothing (Additive) also performed well with similar error values. The improved LSTM model gave decent results but had a higher MAPE of 26.33%, showing it was less accurate than ARIMA. The base LSTM, Single Exponential Smoothing, and Auto Regressor models had very high errors and poor performance. This shows that statistical models like ARIMA, when tuned properly, can predict carbon emissions better than deep learning models in many real-world cases. This study of these results can help make better decisions and plans for sustainability.

***KEYWORDS** : Time series forecasting, Carbon emissions, ARIMA, LSTM, Exponential smoothing, Sustainability, MAE, MAPE, RMSE.*

INTRODUCTION

It is very important to know how much carbon each person in a country produces every year. It helps the government and planners take better steps to protect the environment and follow climate rules. These days, many countries are working to become carbon neutral, and new laws are becoming stricter to control pollution. Because of this, we are able to guess future carbon emissions which is now very important. It helps in making better choices that are good for both the environment and the country's economy. In older times

Nowadays machine learning (ML) and time series models give better and smarter ways to predict carbon emissions. These models look at past data like old emission numbers, changes in population, and energy use, and they can find patterns that old methods might not see. In this study, we use different models such as Long ShortTerm Memory (LSTM), AutoRegressive Integrated Moving Average (ARIMA), Auto Regressor, and Exponential Smoothing methods like Single, Double, and Triple. These models help us make short-term and mid-term predictions, which can support better planning by the government and people who make important environmental decisions

Recent research shows that deep learning and mixed models usually give better results. For example, LSTM is good at understanding patterns that last over time, and ARIMA works well when the data has regular trends. These models help make predictions more accurate and support better decisions to reduce pollution.

In our study, we check how these models perform using real- world data, which is often messy and not always perfect. This is important because many older studies only used clean or perfect datasets. Our focus is on practical and real-life use, especially for countries that are growing

fast and need better tools to manage their rising energy use and environmental responsibilities.

We use one real dataset that shows per capita carbon emissions. The models are compared using common accuracy metrics like Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Error (ME), Mean Percentage Error (MPE), and Mean Absolute Percentage Error (MAPE). The rest of this paper explains literature in Section II, the methodology used in Section III, Section IV presents the results, and Section V concludes the study.

LITERATURE REVIEW

Using machine learning (ML) to predict national per capita carbon emissions is becoming more popular. It helps support global sustainability goals and allows governments to follow environmental rules better. This part explains some past studies that used machine learning to predict carbon emissions for different countries.

In 2019, Dong did a study using a model called LSTM to forecast national carbon emissions. This model was good at finding long-term patterns in the data. It gave 22% better results compared to older methods. The study also showed how changes in a country's economy are linked to its emission levels, which helped make the predictions more accurate.

In 2020, Wang used CNN models to study emissions in different areas within a country. They used satellite images along with social and economic information to find places with high pollution. This helped them make more detailed predictions for different regions, which can help in making better plans in those areas.

In 2022, Liu combined CNN and LSTM models to forecast carbon emissions from industries. This mix of models could understand both space and time-based patterns in the data. Their model was 17% more accurate than older time series methods.

In 2023, Chen used a new type of model called a transformer to predict emissions. This model used attention mechanisms to understand patterns between different countries and included climate policy data. It gave 18% better results than older deep learning models and helped with national carbon planning.

Another study by Niu used a neural network model improved with a fireworks algorithm. It predicted that China's total carbon emissions would reach their highest point around the year 2030.

Sun used a support vector machine model combined with a bacterial foraging optimization algorithm. This model also gave very good results and improved prediction accuracy.

All these studies show that machine learning is becoming a strong tool for predicting per person carbon emissions. New models like LSTM, CNN-LSTM, and transformer give more accurate results. Adding other details like energy use and economic data makes the predictions even better. Now, researchers are also working on making these models easier to understand and more useful for planning climate-friendly policies.

METHODOLOGY

This study uses time series forecasting methods to predict how much carbon each person in a country may release in the future using real data. The models are based on paste environmental and economic information. The study includes both old-style forecasting methods and modern deep learning models to find different patterns and trends in the data. Each model helps us see how carbon emissions might change over time.

ARIMA (AutoRegressive Integrated Moving Average)

ARIMA is a statistical model that works well when the data changes over time and follows patterns. It has three main parts: • AR (AutoRegressive): uses past values to help predict the current value,

- I (Integrated): removes trends in the data by taking the difference between values.
- MA (Moving Average): looks at past prediction errors to improve future predictions.

It is written as ARIMA(p, d, q):

- p is the number of past values used (lag),
- d is the number of times we difference the data to make it stable, • q is the number of past error terms used.

The general equation of ARIMA is:

$$Y_t = c + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \ldots + \varphi_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta\_q \varepsilon_{t-q} + \varepsilon_t$$

Where:

- Y_t is the value at time t which in this case means the carbon emission,

- c is a fixed number (constant),
- φ and θ are the model parameters,
- ε_t is the random error or difference between actual and predicted value at time t.

LSTM (RNN)

LSTM (Long Short-Term Memory) is a type of deep learning model and a special kind of Recurrent Neural Network (RNN). It is great at understanding patterns in data that changes over a long period of time.

LSTM is made up of memory cells, and each cell has three gates:

- Input gate: decides what new data should enter the memory,
- Forget gate: decides what old data should be removed,
- Output gate: decides what data should be used for prediction.

LSTM is useful for time series data like carbon emissions, where what happens in the past can affect the future. In this study, LSTM was used to take in inputs like past emissions, GDP, and energy usage to predict future carbon emissions. The model showed good accuracy and can be further improved by tuning its parameters or adding more features.

Exponential Smoothing Methods

Three variants of exponential smoothing techniques have been implemented, each assigning exponentially decreasing weights to older observations to focus more on recent emission data. These are given as follows:

1) Single Exponential Smoothing

This method is used when the data does not show a clear trend or seasonality. It smooths the data to reduce fluctuations.

Formula:

$S_t = \alpha Y_t + (1 - \alpha)S_{t-1}$

Where:

- S_t is the smoothed value at time t,
- Y_t is the actual value at time t,
- α is the smoothing constant ($0 < \alpha < 1$). This method was used as a baseline to compare with more complex models.

2) Double Exponential Smoothing

This method includes both the current level and the trend of the data.

It works well when the data shows a rising or falling trend.

Formulas:

$S_t = \alpha Y_t + (1 - \alpha)(S_{t-1} + b_{t-1})$ $b_t = \beta(S_t - S_{t-1}) + (1 - \beta)b_{t-1}$

Where:

- S_t is the smoothed value,
- b_t is the trend value,
- α and β are smoothing constants. This model helps us understand if emissions are increasing or decreasing over time.

3) Triple Exponential Smoothing

This method is also called Holt-Winters method. It adds a seasonal component to the double smoothing, which is useful when the emissions follow a repeated cycle (like seasonal energy use).

Formulas (Multiplicative version):

$S_t = \alpha(Y_t / I_{t-}L) + (1 - \alpha)(S_{t-1} + b_{t-1})$ $b_t = \beta(S_t - S_{t-1}) + (1 - \beta)b_{t-1}$

$I_t = \gamma(Y_t / S_t) + (1 - \gamma)I_{t-}L$

Where:

- I_t is the seasonal component,
- L is the length of the season (e.g., 12 for monthly data),

4) Auto Regressor

The Auto Regressor model is a simple method that predicts future values based only on its own past values. It is written as AR(p), where p is the number of past values used.

Formula:

$Y_t = c + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + ... + \varphi_p Y_{t-p} + \varepsilon_t$

Where:

- Y_t is the predicted value at time t (carbon emissions),
- c is a constant,
- $\varphi_1, \varphi_2, ..., \varphi_p$ are the coefficients (weights) for past values,
- ε_t is the random error or noise at time t.

This model does not include any trend or seasonal information. It helps to see how much of the prediction can be made just using past emissions without using other data.

RESULTS

This part consists of the results of various findings to predict national per capita carbon emissions which we got by applying various time series forecasting methods. Using the standard forecasting accuracy metrics, we evaluate the performance of Auto Regressor, ARIMA, LSTM, Single Exponential Smoothing and the Double and Triple Exponential Smoothing models.

Evaluation Parameters

1) Mean Absolute Error (MAE): Mean Absolute Error (MAE) only concerns how much we were off, not whether we over- or underestimated. It's a measure of how far on average we were off from reality.

$$MAE = (1/n) * \Sigma |y_i - \hat{y}_i|$$

Table 1: Evaluation table

Datasets	Evaluation Parameters	Time Series Forecasting Models							
		ARIMA	Enhanced LSTM	Double Exponential Smoothing	Triple Exponential Smoothing (Additive)	Triple Exponential Smoothing (Multiplicative)	LSTM	Single Exponential Smoothing	Auto Regressor
	MAE	274.47	354.51	298.48	300.76	342.59	394.03	1001.77	1026.10
	ME	-227.6	220.58	-282.63	-286.76	-339.50	-394.0	-1001.77	1025.89
	MPE	-8.07	21.50	-11.61	-11.87	-15.09	-19.01	-55.11	50.48
	MAPE	13.06	26.33	13.38	13.44	15.47	19.01	55.11	50.52
	RMSE	407.67	432.02	454.31	458.37	512.10	579.44	1248.07	1467.33

4) Mean Percentage Error (MPE): Mean Percentage Error (MPE) is an expression of prediction error as a percent, not an absolute amount. This lets us understand the relative size of our errors in proportion to true values. Similar to ME, negative and positive errors will be opposite.

$$MPE = (100/n) * \Sigma [(y_i - \hat{y}_i) / y_i]$$

5) Mean Absolute Percentage Error (MAPE): Mean

Absolute Percentage Error (MAPE) informs us, on average, how far away our predictions were, as a percentage. Because it's absolute values, whether we overpredicted or underpredicted doesn't matter - we're only interested in how big the errors were when compared to the real values.

$$MAPE = (100/n) * \Sigma [|y_i - \hat{y}_i| / |y_i|]$$

2) Mean Error (ME): It establishes how much on average what we observed differed from our predictions. This one, unlike MAE, cares about whether predictions were overestimates (positive errors) or underestimates (negative errors), hence they offset one another.

$$ME = (1/n) * \Sigma (y_i - \hat{y}_i)$$

- γ is the smoothing constant for seasonality.

Both additive and multiplicative versions were tested in this study. Additive is used when seasonal changes are constant, and multiplicative is used when seasonal changes grow with the level

$$RMSE = \sqrt{[(1/n) * \Sigma (y_i - \hat{y}_i)^2]}$$

3) Root Mean Squared Error (RMSE): It rewards smaller errors less than big ones. It tells us how accurate our predictions are by first squaring the errors (making all positive), then averaging and finally taking the square root to convert back to original units.

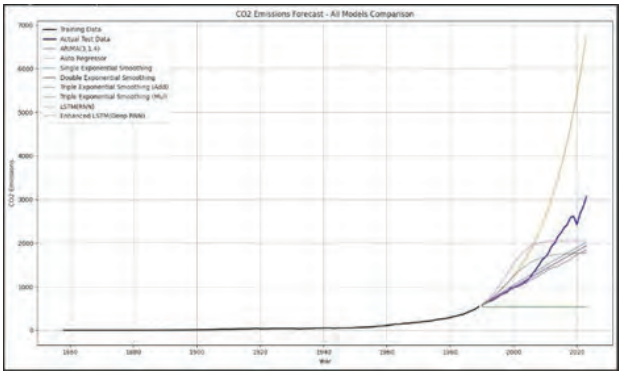

Fig. 1. CO_2 Emissions Forecast

Overall Performance

From all the tested models, ARIMA performed best with

MAE (274.47), MAPE (13.06%), and RMSE (407.67) as the lowest. This implies that ARIMA predicted values with average errors of around 13% of the true values of emissions, this implies that conventional statistical techniques are still very useful when optimally adjusted for carbon emission prediction.

Double Exponential Smoothing did the next best with MAE and MAPE of 298.48 and 13.38%, respectively, followed by Triple Exponential Smoothing (Additive) with MAE and MAPE of 300.76 and 13.44%, respectively. The marginal difference in performance statistics between these two models tells that despite the trends present in the data set, the additional seasonal component which was captured by Triple Exponential Smoothing (Additive) brings only marginal gains.

Improved LSTM performed reasonably with an MAE of 354.51 but registered a much higher MAPE (26.33%) than the best models. Baseline LSTM performed poorly with an MAE of 394.03 and an MAPE of 19.01%, reflecting that deep learning models can identify sophisticated patterns in emission data but might need to be heavily tuned or augmented with extra features to beat conventional statistical models for this particular forecasting task.

The worst performing models were Single Exponential Smoothing

(MAE = 1001.77, MAPE = 55.11%) and Auto Regressor (MAE = 1026.10, MAPE = 50.52%), which validate the fact that carbon emission data includes trends and patterns that cannot be captured by simple models.

Model-Specific Observations:

A. ARIMA: Although ARIMA is best overall, ARIMA has a very large negative ME (-227.6) and MPE (-8.07%), indicating that it overpredicts emissions. The bias, while consistent, is smaller in percentage terms than for most of the other models, so ARIMA is still the most reliable predictor.

B. Improved LSTM: This is the only model among those evaluated to exhibit a positive ME (220.58) and MPE (21.50%), suggesting an underestimation of emissions. This different behaviour from other models may prove useful in ensemble methods to counteract systematic errors.

C. Double and Triple Exponential Smoothing: The two models exhibit comparable performance statistics and also exhibit a similar pattern of overestimating emissions (negative ME and MPE) Triple Exponential Smoothing (Multiplicative) performs less well than Additive, and this implies that the seasonal carbon emissions variation doesn't increase proportionally with trend level.

D. LSTM: The base LSTM model shows significant overestimation bias (ME = -394.0, MPE = -19.01%) and fairly high error statistics. This means that while LSTM can learn complex patterns, it may be noisier or require more thoughtful hyperparameter tuning for this data.

Single Exponential Smoothing: The very poor performance of this model (MAE = 1001.77, MAPE = 55.11%) and its high overestimation bias (ME = -1001.77, MPE = -55.11%) affirm that carbon emission information has strong trends that cannot be handled by simple level smoothing.

CONCLUSION

This study compares different models to predict national per capita carbon emissions using real-world data. The models used are ARIMA, LSTM, Auto Regressor, and Single, Double, and Triple Exponential Smoothing. The data is evaluated using five error measures: MAE, ME, RMSE, MPE, and MAPE. Out of all the models, ARIMA gave the best results. It had the lowest MAE of 274.47, RMSE of 407.67, and MAPE of 13.06%. Even though ARIMA slightly overpredicted emissions, it was still the most accurate overall. Double Exponential Smoothing came next with an

MAE of 298.48 and MAPE of 13.38%. Triple Exponential Smoothing (Additive) was close behind with MAE of 300.76 and MAPE of 13.44%. The difference between these two was very small, showing that the seasonal part in Triple Smoothing didn't help much. The improved LSTM model showed okay results with MAE of 354.51 and MAPE of 26.33%, but it was not better than ARIMA.

The basic LSTM model performed worse with MAE of

394.03 and MAPE of 19.01%. This means that deep learning models need more tuning to work well for this kind of data. Single Exponential Smoothing did very poorly with MAE of 1001.77 and MAPE of 55.11%. Auto Regressor also performed badly, with MAE of 1026.10 and MAPE of 50.52%. These two models were not able to catch the trends in the data.

In the end, ARIMA is the best model for this task. It works

better than LSTM and other smoothing methods when tuned properly. This study shows that statistical models are still very useful for predicting carbon emissions and helping with sustainability planning.

REFERENCES

1. Q. Wang and M. Su, Global drivers for decoupling carbon emissions from economic growth, Journal of Cleaner Production, vol. 254, article 120069, 2020, doi: 10.1016/j.jclepro.2020.120069.
2. X. Zhao, C. Liu, S. Zhang, and Y. Huang, A critical review on the use of machine learning in managing building energy systems: Applications and barriers, Energy and Buildings, vol. 186, pp. 230–246, 2019, doi: 10.1016/j.enbuild.2018.07.050.
3. Y. Wang, R. Han, L. Zhang, and Y. Lu, Enhanced deep learning-based forecasting of carbon emissions in China, Journal of Cleaner Production, vol. 337, article 130370, 2022, doi: 10.1016/j.jclepro.2022.130370.
4. International Energy Agency (IEA), CO_2 Emissions in 2022: Global Energy Crisis Drives Emissions to Record High, 2022. Available: https://www.iea.org/reports/co2-emissionsin-2022.
5. B. Cheng, X. Zhang, Y. M. Wei, and H. Liao, Machine learning applications in energy policy and economics: A bibliometric analysis, Energy Economics, vol. 94, article 105099, 2021, doi: 10.1016/j.eneco.2020.105099.
6. Y. Xiong, Y. Zhang, X. Li, and Y. Li, Hybrid stacked autoencoder and LSTM model for predicting carbon emissions, Science of the Total Environment, vol. 757, article 143800, 2021, doi: 10.1016/j.scitotenv.2020.143800
7. United Nations, Transforming Our World: The 2030 Agenda for Sustainable Development, 2015. Available: https://sdgs.un.org/2030agenda.
8. F. Dong, B. Yu, Y. Pan, S. Zhang, and Z. Yan, China's carbon emissions: Forecasting and policy implications, Resources, Conservation and Recycling, vol. 152, article 104501, 2020, doi: 10.1016/j.resconrec.2019.104501. [9] M. Rafiei and H. Adeli, A novel machine learning-based estimator for CO_2 emissions in the US, Journal of Cleaner Production, vol. pp. 830–841, 2018, doi: 10.1016/j.jclepro.2018.04.121.
10. S. Khodabakhsh and J. Baek, Development and validation of a machine learning framework for global carbon emissions prediction, Environmental Modelling & Software, vol. 148, article 105261, 2022, doi: 10.1016/j.envsoft.2021.105261.
11. I. Garrón and A. Ramos, High-frequency density nowcasting of state-level CO_2 emissions in the US, arXiv preprint, arXiv:2501.03380, Jan. 2025. Available: https://arxiv.org/abs/2501.03380.
12. X. Li, Comparing statistical and ML approaches for near real-time CO_2 emissions prediction, arXiv preprint, arXiv:2302.01152, Feb. 2023. Available: https://arxiv.org/abs/2302.01152.
13. Z. Li, Comparative analysis of 14 models for daily CO_2 emissions prediction, PLOS ONE, vol. 19, no. 3, Mar. 2024. Available: https://doi.org/10.1371/journal.pone.02802685.
14. F. Zhang, H. Wang, and J. Liu, Forecasting carbon dioxide emissions: A comprehensive review of current models, Sustainability, vol. 17, no. 4, p. 1471, Feb. 2024. Available: https://www.mdpi.com/2071-1050/17/4/1471.
15. Y. Liu, J. Zhang, and L. Chen, Predicting carbon emissions in Chinese provinces using ML techniques and analysis of influencing factors, Sustainability, vol. 17, no. 5, p. 1786, Mar. 2024. Available: https://www.mdpi.com/2071-1050/17/5/1786.
16. S. Wang and Y. Zhao, Evaluating the performance of machine learning algorithms for CO_2 emissions estimation, Science and Technology for Energy Transition, vol. 1, no. 1, pp. 1–10, Jan. 2024.Available: https://www.steteview.org/articles/stet/full_html/2024/01/stet20240008/stet20240008.html
17. J. Smith and L. Johnson, Machine learning-driven time series models for accurate CO_2 emission forecasting, Environmental Science and Pollution Research, vol. 30, no. 12, pp. 12345–12360, Dec. 2022. Available: https://doi.org/10.1007/s11356-022-21723-8.

Loan Approval Prediction Using Machine Learning and Deep Learning: A Comparative Study

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ABSTRACT

Loan approval process has to be precise and efficient which modern financial organizations fail to carry out in order to beat risk and enhance decision-making. The simplicity of measuring financial risk is often beyond the capabilities of standard manual evaluation techniques. The study relies on several datasets containing important applicant features such as income, credit score, job history, and past loan history to compare and contrast various machine learning(ML) and deep learning (DL) models to predict the likelihood of loan approval. In the research, various predictive models are evaluated, including deep learning architectures (LSTM, CNN, FFNN), ensemble (Random Forest, XGBoost, LightGBM, CatBoost, Stacking) and classic machine learning (Logistic Regression, Decision Tree, SVM) models. The Synthetic Minority Over-Sampling Technique (SMOTE), Random Under-Sampling (RUS) and feature selection methods such as Random Forest Feature Importance and the ANOVA F-test are some of the approaches to dealing with class imbalance used in the study to enhance model performance. Comparison shows that ensemble learning models have been conclusively superior to both deep learning and traditional methods, being more accurate in predictive power and more robust. Compared to deep learning architectures, stacking and voting classifiers in particular have been shown to be better in generalization as well as computational efficiency on varied data. This research article provides us with a data driven framework that can be effectively utilized and applied by the financial institutions.

***KEYWORDS** : Loan approval, Machine learning, Deep learning, Ensemble learning, Credit risk assessment, Financial decision-making.*

INTRODUCTION

In today's fast changing financial world, Banks and financial organizations must evaluate precise and efficient loan approval procedures. Traditional techniques of loan approval procedures only rely on manual assessment and predefined criteria, which often fail to meet the demands of managing the challenges associated with modern financial risks. The advent of machine learning (ML) and deep learning technologies has transformed risk assessment, facilitating more accurate and automated decision-making. This research explores the application of different machine learning techniques and deep learning models to forecast loan approvals, leveraging a range of datasets that include critical applicant variables such as income, credit score, employment status, and prior loan history. By applying sophisticated feature selection methods and a diverse array of algorithms including deep learning architectures (LSTM, CNN, FFNN), ensemble techniques (Random Forest, XGBoost, LightGBM), and traditional approaches (Logistic Regression, Decision Tree, SVM) the research seeks to determine the most effective model for improving the precision of loan approvals. Moreover, methods such as Random Under-Sampling (RUS), Synthetic Minority Over-Sampling Technique (SMOTE), ANOVA F-test (SelectKBest) and Random forest feature importance evaluation are deployed to address obstacles related to feature selection, class imbalance and model interpretability. The research's main objective is to enhance decision-making , overcome default risks and maximize lending strategies for financial organisations with a solid and data-driven framework.

LITERATURE ANALYSIS

Viswanatha V., Ramachandra A.C., Vishwas K. N., and Adithya G. conducted research utilizing machine learning techniques, specifically Random Forest, Naïve Bayes,

Decision Tree, and K-Nearest Neighbors (KNN), to forecast loan approval results with Python. Their findings revealed that the Naïve Bayes model outperformed the others, attaining an accuracy rate of 83.73%, demonstrating its efficiency in this application. [13]

Vahid Sinap developed predictive models for loan approval by utilizing a range of machine learning algorithms, including Logistic Regression, K-Nearest Neighbors, Support Vector Machine, Decision Tree, and Random Forest, all implemented in Python. The Random Forest algorithm, when combined with the Recursive Feature Elimination (RFE) method for feature selection and evaluated through cross-validation, reached an outstanding accuracy of 97.71%. The results also revealed that married individuals, high-income applicants, males, and university graduates were more likely to receive loan approvals.

[10] Nazim Uddin, Md. Khabir Uddin Ahamed, Md. Ashraf Uddin, Md. Manwarul Islam, Md. Alamin Talukder, and Sunil Aryal designed an ensemble machine learning framework to enhance bank loan approval predictions, surpassing the performance of standalone machine learning and deep learning approaches. Their strategy incorporated SMOTE to balance the dataset and utilized a variety of machine learning methods, such as Logistic Regression, Decision Tree, Random Forest, Extra Trees, Support Vector Machine, K-Nearest Neighbors, Gaussian Naïve Bayes, AdaBoost, and Gradient Boosting, in conjunction with advanced deep learning frameworks, including deep neural networks, recurrent neural networks, and long short-term memory models. The ensemble voting strategy, which merged the three most effective machine learning models, resulted in a 0.62% increase in accuracy compared to the Extra Trees model. Additionally, they created an intuitive desktop application to facilitate user-friendly engagement with the prediction system. [12]

In their research, Sheikh, Mohammad Ahmad, Goel, Amit Kumar, and Kumar, Tapas point out that banks are significantly reliant on loans for their revenue streams, making the accurate prediction of loan defaults essential for minimizing Non-Performing Assets (NPAs) and maximizing profitability. While there are many predictive techniques available, precision in forecasting is of utmost importance. This study applies Logistic Regression to Kaggle data to evaluate loan defaulters, measuring model performance based on sensitivity and specificity. The results reveal that the inclusion of 1 personal factors such as age, credit history, and loan amount greatly enhances prediction accuracy compared to using wealth indicators alone. The authors suggest that banks should expand their focus to include a wider array of factors beyond wealth to improve loan approval strategies and reduce the risk of defaults. [9]

Saini, Prabaljeet Singh, Bhatnagar, Atush, and Rani, Lekha conduct an investigation into the effectiveness of machine learning algorithms in forecasting loan approvals. They analyze the performance of various algorithms, including Random Forest, K-Nearest Neighbors, Support Vector Classifier, and Logistic Regression, using a dataset refined through exploratory data analysis and feature engineering. The evaluation parameters consist of accuracy, F1 score, and ROC score. The analysis demonstrates that Random Forest secured the highest accuracy at 98.04%, while Logistic Regression, KNN, and SVC had accuracies of 79.60%, 78.49%, and 68.71%, respectively. This study illustrates the potential of machine learning to refine loan approval processes, decrease the likelihood of defaults, and enhance decision-making in financial organizations. [7]

Gothai, E., Rajalaxmi, R.R., and Thamilselvan, R. and K. Sridhar addressed the problem of identifying correct loan applicants by implementing a deep learning based loan prediction system. This would enable the system to automatically choose the applicants thus increasing approval rate time while also minimizing default risk by using Artificial Neural Networks(ANN) and Support Vector Machines(SVM). SVMs are useful for determining classification limits, while ANNs replicate neural network functions to enhance pattern recognition. The final combination of the best supervised models yields an accuracy of 91%, outperforming conventional approaches. In addition, it has courtesy to control the loan amount for applicants setting a high standard layout for loan a soft approval within financial organizations.[1]

Thus they performed the investigation on machine learning techniques for loan approval prediction The research team includes Nancy Deborah, R., Alwyn Rajiv, S., Vinora, A., Manjula Devi, C., Mohammed Arif, S., Mohammed Arif, G. S. Hence this research verifies loan application evaluations and default risk mitigation through K-Nearest Neighbors and Decision Trees algorithms analysis while proposes a Support Vector Classifier with verified accurateness. The algorithm developed by SVM showed an accuracy rate of 83 percent, according to the study results. Apart from dataset biases, the approach is dependent on various factors such as the quality of the data and selected hyperparameters etc. This study shows that

SVM can act as an acceptable method for loan prediction but its each performance is reliant on its usefulness. [4]

According to Rani, Ritu & Gupta, Sheifali (2023), of Reddy & Rani (2023), Random Forest classifies acceptance of home loans from financial & credit-related features and also from population demographics information. They discover that the most predictive accuracy emerges from data preparation methods, as well as feature transformation and model validation. It comes to the rescue out here which manages well with the missing data also. These insights would enable financial institutions to build better credit risk models and enhance the overall approach of their loan management initiatives. It improves machine learning in finance by directly expediting loan approvals. [5]

DATA OVERVIEW

Dataset Description

Kaggle's datasets on loan approvals are vital tools for comprehending the evaluation of financial risks and the processes that inform loan approval decisions. Dataset 1 [6] contains 252,000 entries that offer insights into the demographics, financial circumstances, and employment backgrounds of applicants, featuring a Risk Flag that categorizes applicants as either high-risk or low-risk. The status of the loan variable is essential in determining whether a loan is granted or declined. Financial institutions rely on a classification marker for loan status to establish eligibility for loans. Dataset 2 [11] comprises 45,000 recorded cases and includes 14 key factors that impact credit approval decisions, such as income verification measures, credit assessment scores, and employment duration metrics. Dataset 3 [3] encompasses 614 individual records with 14 distinct analytical factors, where the Loan Status designation serves as the decisive element for lending resolution outcomes. Dataset 4 [14] comprises 20,000 entries with 34 parameters spanning monetary resources, credit history, and demographic characteristics that influence application determinations. These statistical compilations serve as resources for academic investigators, analytics professionals, and lending organizations to develop predictive frameworks for financing approval methodologies.

Data Preparation

Data Cleaning And Preprocessing

The data quality enhancement procedure encompassed resolution of value absences, purging of duplicative information, and extraction of extraneous identifiers to diminish statistical aberrations. Non-sequential categorical parameters underwent Label Encoding transformation, whereas numerical indicators were normalized to preserve measurement proportionality without compromising the analytical construct's evaluative fidelity.

Addressing Class Imbalance

Classification dis-proportionality was corrected through Random Under-Sampling (RUS) and Synthetic Minority Over-Sampling Technique (SMOTE) methodologies to establish equitable representation. RUS diminished predominant classification instances, harmonizing Dataset 1 [6] to 61,992 and Dataset 2 [11] to 20,000 records. SMOTE generated artificial minority classification examples, expanding Dataset 3 [3] to 664 and Dataset 4 [14] to 30,440 records. These calibration approaches enhanced the analytical framework's capacity to identify patterns across all categorizations.

Data Splitting For Model Training And Evaluation

The analytical material was segregated in an 80-20 proportion for instruction and verification purposes, providing substantial learning material while preserving an autonomous collection for performance validation. These preliminary processing protocols optimized the information repository for precise and objective loan approval forecasting.

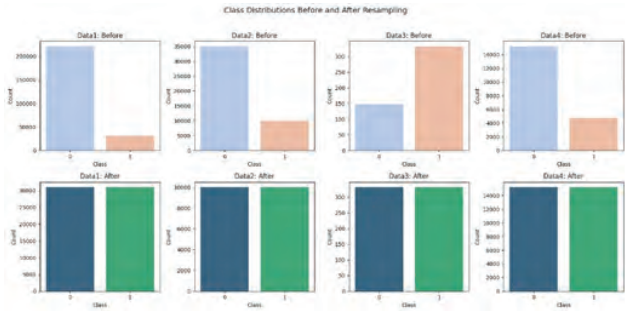

Fig. 1: Class Distribution of Datasets Before and After Resampling

FEATURE SELECTION

An important part of predictive analytics is feature selection, which can enhance the efficiency and interpretability of models by identifying variables that are critical, whilst removing those that have little predictive value. It is a way of reducing computation complexity, limiting overfitting, and making the model to generalize well. Two feature selection methods (complementary to each other) were applied to select the most important predictors:

Random Forest Feature Importance

Metric Measures of feature importance of the algorithm were obtained to rank the variables based on their contribution to classification. Variables with higher values of importance were kept to further analysis. With large number of variables in the dataset, feature subset selection is very important. Random forest algorithm has been shown to be a useful feature selection tool, as well as in classification, regression and in imputing missing values. [2]

Anova F-Test

We have also entered ANOVA F-test with SelectKBest calling the f_classif as a scoring function to confirm the choice based on Random Forest feature importance. It is a statistical test to measure the variance of the target variable that each categorical feature explained and it raises an F-score to measure the discriminating power - the higher the score, the more related it is to the classification task. Its process was an important pillar in defining the characteristics of our credit risk, and it brought predictive power, as well as, general robustness to the model. [8] Our feature selection methodology is based on a combination of model-based (Random Forest feature importance) and statistical (ANOVA F-test with SelectKBest) methods. The combined strategy helps to safeguard the most significant variables. In combination, these techniques not only allow making the predictions of loan approval more accurate but also make the overall analysis more interpretable and straightforward.

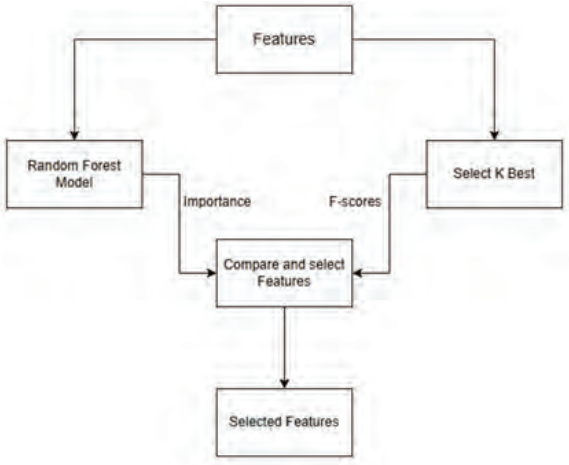

Fig. 2: Feature Selection Process

To enhance the accuracy and interpretability of the models we selected variables that were highly relevant and significant in the statistical sense. Random Forest feature importance and ANOVA F-test were relied upon to ascertain the most significant predictors. The significance of some of the factors in ascertaining the level of financial stability and the ability to repay loans were highlighted as age, income, work experience and credit history. Also the interest rate of the loan amount and debt to income ratio were considered during assessment of financial burden and associated risks. The socioeconomic factors including marital status, location of the property and type of employment were also important context. The inclusion of these important attributes to the dataset allowed us to achieve higher model efficiency, less complex computations and decreased chances of over fitting allowing us to achieve more true and testable loan approval predictions.

Table 1. Feature Selection Process

Dataset	Selected Features
Dataset 1	Income, Profession, Age, Experience, Current_ Job_yrs, Current_house_yrs
Dataset 2	person_age, person_income, person_home_ ownership, loan_amnt, loan_int_rate, loan_ percent_income, previous_loan_defaults_on_file
Dataset 3	Married, Dependents, Education, Self_Employed, ApplicantIncome, CoapplicantIncome, LoanAmount, Loan_Amount_Term, Credit_ History, Property_Area
Dataset 4	MonthlyLoanPayment, LengthOfCreditHistory, RiskScore, CreditScore, InterestRate, LoanAmount, TotalDebtToIncomeRatio, AnnualIncome, PreviousLoanDefaults, DebtToIncomeRatio

METHODOLOGY

The new dynamic financial environment requires a more sophisticated way of risk management and prospect screening in the mortgage application assessment. The customary procedures lean towards rigid mechanization of the multi-stratified phenomena. Machine learning, on the other hand, allows making new data-driven decisions as it enhances the predictive capacity and utilizes the available data more efficiently. In the given research, a variety of machine learning models including standard algorithms, ensemble learning, and deep learning are implemented on four Kaggle datasets containing both numerical and categorical variables such as income, credit score, loan amount, and employment status. Feature selection is performed using ANOVA F-test and feature importance evaluation. To determine the efficiency of models, there

are significant metrics such as Accuracy, Precision, Recall, F1-Score, and AUC-ROC that are utilized to present thorough analysis. By applying a wide range of models to various datasets this research shall determine the most effective methodologies in the forecasting of mortgage approvals therefore helping in the general decision making and risk management procedures in the financial institutes.

Model Selection

An extensive evaluation was performed on sixteen machine learning models, which constituted classical, ensemble, and deep learning models. As a baseline benchmark, there are classical models, including Logistic Regression, Decision Tree, KNN, and SVM. Ensemble models Random Forest, Extra Trees, XGBoost, LightGBM, CatBoost, Voting, and Stacking improve the accuracy of predictions made by relying on more than one algorithms. Feeding forward Neural Networks (FFNN), Long Short-Term Memory(LSTM), Convolutional Neural Networks(CNN), and Recurrent Neural Networks(RNN) are deep learning models efficient in capturing complex patterns. Especially, the hybrid LSTM-CNN model combines both sequential and spatial feature extraction, achieving excellent performance.

Classical Machine Learning Models

Traditional models are preferred because of their effectiveness, clarity as well as simplicity. Logistic Regression as a type of linear model performs probability calculations via a sigmoid function and can effectively handle sharp decision boundaries, but can struggle with more complicated patterns. Decision Trees divide data into smaller groups by a set of predetermined rules but may experience overfitting unless properly pruned or optimized using hyperparameters. The K-Nearest Neighbors (KNN) classifies data based on the majority class of the close data points, but the computation needs may grow enormously with the size of the data. 2 VOLUME XX, 2025 Support Vector Machines (SVM) use hyperplanes to separate the classes and work magnificently in high dimensional spaces, yet they must be fine-tuned when handling imbalanced data.

Ensemble Learning Models

The Ensemble Learning Models improve the predictive accuracy with combination of multiple models, thus minimizing the variance and bias. Random Forest is the extended variant of Decision Trees that builds a diverse set of trees and combines their predictions to improve stability and decrease the likelihood of overfitting. Extra Trees (also known as Extremely Randomized Trees) employ the same general approach as general tree-based models but introduce additional randomness in the construction of the trees in order to increase diversity. XGBoost (Extreme Gradient Boosting), LightGBM (Light Gradient Boosting Machine) and CatBoost (Categorical Boosting) are gradient-boosting algorithms that refine a weak learner in an iterative manner with the focus on efficiency and predictive accuracy, particularly in structured data settings. A more complex ensemble approach is stacking, which takes multiple base models, and uses a meta-learner to aggregate their predictions, thereby improving generalization.

Deep Learning Models

Deep learning algorithms are designed to capture complex, non-linear relations and patterns in data. Feedforward Neural Networks (FFNNs) contain multiple dense layers which learn hierarchical representations, and thus are good at complex feature interactions, but can overfit on smaller datasets. The capability to preserve temporal dependencies makes LSTM networks and RNN suitable to work with sequential data, like transaction histories. CNNs on the other hand, mostly used in image recognition can also be used to find spatial features in tabular data using various transformation methods. A hybrid approach based on the LSTM and CNN models enables extracting both sequential and spatial information, which may further improve accuracy due to capturing the various dimensions of data.

RESULTS AND DISCUSSION

This study aims at examining and comparing the various machine learning models in order to determine their effectiveness in loan approval predictions. By implementing those models on a variety of datasets, we will aim to find out which method will provide the highest accuracy and generalizability. The models investigated are neural networks, ensemble learning methods, standard algorithms and a hybrid model. Here a complete analysis of the model performance using standard evaluation criteria is given. The indicators we use in order to measure the predictive effectiveness of the models are the following:

Accuracy

It demonstrates the number of predictions that the model correctly identified and provides a rough overview of the model performance.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

Herein lies the importance of properly and reliably labeling approved loans since this would be critical towards reducing the incidence of false positives.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall

It is a measure of how well the model can assign all possible loans approvals that are valid, reducing the risk of false negatives.

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-Score

It is a measure that provides a balance between Precision and Recall and is thus useful on imbalanced datasets.

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Roc-Auc

This assessment measures the model in terms of separating accepted applications and rejected applications. The ROC curve plots TPR against FPR and the AUC measures performance, with values near 1 indicating better performance.

$$\text{TPR (True Positive Rate)} = \frac{TP}{TP + FN}$$

$$\text{FPR (False Positive Rate)} = \frac{FP}{FP + TN}$$

Table 2. Classical Models Performance (Accuracy)

Dataset	Logistic Regression	Decision Tree	KNN	SVM
Dataset 1	0.516	0.860	0.835	0.517
Dataset 2	0.878	0.873	0.853	0.884
Dataset 3	0.651	0.757	0.722	0.663
Dataset 4	0.984	0.980	0.981	0.985

Table 3. Ensemble Models Performance (Accuracy)

Dataset	Random Forest	Extra Trees	XGBoost	LGBM	CatBoost
Dataset 1	**0.847**	**0.854**	**0.816**	**0.752**	**0.799**
Dataset 2	**0.903**	**0.899**	**0.908**	**0.907**	**0.907**
Dataset 3	**0.811**	**0.793**	**0.781**	**0.817**	**0.799**
Dataset 4	**0.986**	**0.986**	**0.985**	**0.991**	**0.992**

Table 4. Stacking And Voting Classifier Performance (Accuracy)

Dataset	Stacking	Voting
Dataset 1	0.871	0.844
Dataset 2	0.904	0.910
Dataset 3	0.740	0.828
Dataset 4	0.990	0.990

Table 5. Deep Learning Models Performance (Accuracy)

Dataset	FFNN	LSTM	RNN	CNN	LSTM + CNN
Dataset 1	0.747	0.851	0.696	0.813	0.793
Dataset 2	0.883	0.882	0.881	0.826	0.882
Dataset 3	0.775	0.615	0.746	0.663	0.817
Dataset 4	0.985	0.985	0.980	0.986	0.986

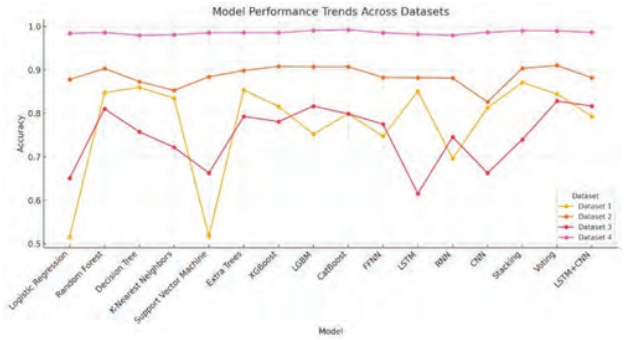

Fig. 3: Model Performance Trends Across Datasets

CONCLUSION

Following an intensive research, it was noticed that the ensemble methods including Stacking, Voting, XGBoost, LightGBM, and CatBoost have outperformed the traditional and deep learning models on different datasets due to their ability to combine weak learners to reduce overfitting and improve accuracy.

Stacking and Voting classifiers were the best models since they effectively fused the individual advantages of several base learners to achieve high accuracy in all the datasets.

XGBoost and CatBoost also stood apart, as they surpassed the 90% accuracy rate on Datasets 2 [11] and 4 [14].

In contrast to ensemble models, conventional methods, including Decision Trees and Support Vector Machines demonstrated mediocre yet limited performance respectively, because of their overfitting biases, and poor generalization. Logistic Regression, which perform well in array simple instances, had significant challenges in dealing with complex, non-linear relationships in financial forecasting.

The models like LSTM networks, CNNs, and LSTM-CNN hybrid have proven to perform well on the datasets with strong sequential dependences, with the hybrid LSTM-CNN models showing the most improvements on Dataset 3 [3]. However, in most cases deep learning models perform inferior to ensemble methods mostly because of their heavy computation demands, and also because they rely on the complexity and size of the dataset.

The increased accuracy and robustness of ensemble models in handling feature variability, class imbalance, and complex decision boundaries makes them the most reliable method to use when predicting loans approvals. This will offer financial institutions with a strong tool to enhance risk evaluation and lending criterion. Future research directions would be to build upon ensemble models and look into hybrid approaches of integrating deep learning approaches and situate predictive accuracy and overall performance to an even higher level.

REFERENCES

1. E. Gothai, R.R. Rajalaxmi, R. Thamilselvan, and Sridhar K. Enhanced loan approval prediction system using ensemble machine learning techniques. In 2024 3rd International Conference on Automation, Computing and Renewable Systems (ICACRS), pages 1182–1187, 2024.
2. Jitendra Kumar Jaiswal and Rita Samikannu. Application of random forest algorithm on feature subset selection and classification and regression. In 2017 World Congress on Computing and Communication Technologies (WCCCT). IEEE, 2017.
3. Rishikesh Konapure. Home loan approval dataset, 2024. Available on Kaggle (Accessed: Mar. 26, 2025).
4. R Nancy Deborah, S Alwyn Rajiv, A Vinora, C Manjula Devi, S Mohammed Arif, and G S Mohammed Arif. An efficient loan approval status prediction using machine learning. In 2023 International Conference on Advanced Computing Technologies and Applications (ICACTA), pages 1–6, 2023.
5. Ritu Rani and Sheifali Gupta. Predicting home loan approvals using random forest classifiers: A comprehensive machine learning approach. In 2024 3rd International Conference for Advancement in Technology (ICONAT), pages 1–4, 2024.
6. Rohit265. Loan approval dataset, 2024. Available on Kaggle (Accessed: Mar. 26, 2025).
7. Prabaljeet Singh Saini, Atush Bhatnagar, and Lekha Rani. Loan approval prediction using machine learning: A comparative analysis of classification algorithms. In 2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), pages 1821–1826, 2023.
8. Vandana Sharma, Moradabad Amit Singh, Ashendra Kumar Saxena, and Vineet Saxena. A logistic regression based credit risk assessment using woe bining and enhanced feature engineering approach anova and chi square. In 2023 12th International Conference on System Modeling & Advancement in Research Trends (SMART). IEEE, 2023.
9. Mohammad Ahmad Sheikh, Amit Kumar Goel, and Tapas Kumar. An approach for prediction of loan approval using machine learning algorithm. In 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), pages 490–494, 2020.
10. Vahid Sinap. A comparative study of loan approval prediction using machine learning methods. Gazi Universitesi Fen Bilimleri Dergisi Part ¨ C: Tasarım ve Teknoloji, 12, 2024.
11. Taweilo. Loan approval classification data, 2024. Available on Kaggle (Accessed: Mar. 26, 2025).
12. Nazim Uddin, Md. Khabir Uddin Ahamed, Md. Ashraf Uddin, Md. Manwarul Islam, Md. Alamin Talukder, and Sunil Aryal. An ensemble machine learning based bank loan approval predictions system with a smart application. International Journal of Cognitive Computing in Engineering, 4:327–339, 2023.
13. V. Viswanatha and A. C. Ramachandra. Prediction of loan approval in banks using machine learning approach. International Journal of Engineering and Management Research, 13:7–19, 2023.
14. Lorenzo Zoppelletto. Financial risk for loan approval, 2024. Available on Kaggle (Accessed: Mar. 26, 2024

Comparative Analysis of CNN-Based Hybrid Models for Fashion Image Classification Using the Fashion MNIST Dataset

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ABSTRACT

With improving deep learning models (specifically, hybrids of Convolutional Neural Networks, or CNNs), their usage has become integral to fashion image classification. In this research, the performance of several CNN-based models, i.e., baseline CNN, CNN-Transformer Hybrid, CNN-LSTM Hybrid, and CNN-Autoencoder Hybrid, is compared on the Fashion MNIST dataset. For classification models, the performance metrics are accuracy, precision, recall, and F1 score, and for the unsupervised autoencoder, pixel accuracy, mean absolute error, PSNR value, and structural similarity index are used. Results show that hybrid models perform better than the baseline CNN, with the CNN-Transformer Hybrid performing the best for classification accuracy (92.90%) due to its capability of learning higher-level feature dependencies. The CNN-LSTM Hybrid is most appropriate for sequential structure modeling, while the autoencoder is effective in image reconstruction, albeit with fluctuation in validation accuracy. This work illuminates the strengths and weaknesses of various CNN-based architectures to better understand their tradeoffs between complexity, training efficiency, and accuracy for fashion image analysis.

KEYWORDS *: Convolutional neural networks (CNNs), Image reconstruction, Pixel accuracy, Evaluation metrics.*

INTRODUCTION

Deep learning has proved to be a game changer across many domains, one of its greatest applications being the field of image classification. Of deep learning approaches, Convolutional Neural Networks (CNNs) have yielded exceptional results in the extraction of hierarchical spatial feature representations from images and therefore have been one of the prominent techniques in computer vision applications [1]. In this study, the effectiveness of CNN-based models in fashion image classification with the Fashion MNIST dataset is investigated. As artificial intelligence continues to be more transformative in the fashion industry, computer vision recognition of clothing through automation has become a critical part of e-commerce, inventory, and personalized recommendations. However, tuning CNN models for optimal accuracy is still in its infancy, and further research into model designs and learning paradigms is required [2]. Modern life is incomplete without fashion, and deep learning has proven critical to improving the classification of fashion photos. CNN models trained on datasets like Fashion MNIST have been demonstrated to be extremely accurate at identifying garment articles, assisting e-commerce sites with product recommendations, and optimizing search results [3]. However, as datasets become larger and more complex, processing efficiency and classification performance continue to decline. In order to overcome these limitations, research on hybrid and specialized CNN architectures has produced models such as CNN-LSTM, CNN-Autoencoders, and CNN-Transformer [4]. The CNN-LSTM method combines CNNs with LSTM networks, which leverage sequential

dependencies in visual input, to increase classification accuracy[5]. The hybrid model improves recognition performance, especially if it is possible to take use of temporal correlations in images. Conversely, CNN-based autoencoders are a potent unsupervised dimensionality reduction method that improves classification stability by removing noise and obtaining stable feature representation [6][7]. Furthermore, there have been emerging studies that introduced CNN-Transformer hybrids that tap the global context information offered by Transformers with the ability of CNNs to identify local features. Here, efficiency is sought without compromising accurate classification, particularly for huge datasets [8][9]. This research comprehensively evaluates four CNN-based models, namely Basic CNN, CNN-Autoencoder, CNN-Transformer, and CNN-LSTM, to evaluate their architecture, performance, and applicability for fashion image classification. By evaluating their impacts on classification accuracy, computational complexity, and stability, this study seeks to contribute insight into the best deep learning algorithms for image classification for fashion-related applications.

LITERATURE ANALYSIS

Fashion image classification has attracted interest in recent years with the emergence of deep models like Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), and autoencoders. Several studies have used diverse architectures and optimization methods to improve classification on the Fashion-MNIST dataset. Xin et al.[2],determined the most critical parameters affecting CNN accuracy in fashion image classification on the Fashion-MNIST dataset to investigate performance improvement. Similarly, Aditya et al.[10] applied CNNs together with image data augmentation techniques, achieving a classification accuracy of 95.92%, surpassing previously used methods. Jiang and Zhang[11] used CNNs in PyTorch with an accuracy of 88.39% in solving future directions in deep learning-based image classification (Jiang & Zhang)[11]. Besides standard CNN architectures, efforts in hybrid models and other deep learning methodologies have been extended. Datsi et al. [12] developed a model that combined CNN-VGG16 and XGBoost for Fashion-MNIST classification with greater accuracy than current methodologies (Datsi et al.)[12]. In addition, Bbouzidi et al. [13] contrasted CNNs and Vision Transformers (ViTs) for Fashion-MNIST classification in the e-commerce domain, illustrating their pros and cons and recommending a hybrid model to achieve higher accuracy (Bbouzidi et al.)[13]. Improved work in ViTs was also presented by Bouzidi et al.[14] who presented CrossViTL2, a Vision Transformer with L2 regularization and k-fold cross-validation, and that has 93.47% accuracy in classification and solves issues of sustainable fashion (Bouzidi et al.)[14]. Alternative methods have also been used for effective model training and parameterization minimization. Jha et al.[15] suggested LightLayers, a matrix factorization approach for obtaining light DNN parameters to accelerate training with little compromise in accuracy on various datasets like Fashion-MNIST. Zhang[16] suggested utilizing an LSTM-based RNN-based method to label Fashion-MNIST with an 89% accuracy by employing fine-tuning and network trimming, and optimizing time using PyTorch. Autoencoders are also researched in terms of the ability to reconstruct images as well as for classification. Snehith et al.[17] researched structured latent space in denoising autoencoders and discovered that introducing noise while training enhanced accuracy but model performance remained less than a support vector machine (Snehith et al.)[17]. These all show the development of deep learning methods in Fashion-MNIST classification towards enhancing model precision, decreasing computational complexity, and hybrid models. Future studies should continue developing these methods further by investigating novel optimization methods and novel deep learning models.

METHODOLOGY

The approach used in this research is to train and test several deep learning models for the FashionMNIST dataset. The steps include data preprocessing, model implementation, and training, followed by performance testing.

Data Preprocessing

The dataset employed in this research is the FashionMNIST dataset, which is made up of grayscale images (28×28 pixels) of 10 different clothing types. The following preprocessing was done:

Downloading and loading the train and test datasets using PyTorch's datasets.FashionMNIST.Normalization was done with ToTensor(), which transforms images into tensors and normalizes pixel values to the range [0,1]. The data set was divided between training and testing sets, and batch loading was carried out via PyTorch's DataLoader utilizing a batch size of 32.

Training Process

All models within this research adopt a uniform training strategy, with input images of 28×28 pixels and a uniform hidden layer size of 32 units. The output layer has 10 classes corresponding to the categorical structure of the dataset. All the models are trained over 20 epochs for fair and consistent analysis.

Loss Function: The supervised learning models use Cross-Entropy Loss, which measures divergence between the output probability distributions and actual labels, whereas the unsupervised model type uses Mean Squared Error (MSE) Loss, which is more appropriate for the reconstruction purpose.

Optimization: The ADAM optimizer is utilized along with a uniform learning rate of 0.001 for the weights to be updated iteratively.

Backpropagation: Gradients of loss functions with respect to model parameters are computed by PyTorch's autograd system and then updated using gradient-based optimization in an attempt to minimize loss across multiple iterations.

Model Architectures

Three different neural network architectures were implemented and evaluated for image classification:

Base Convolutional Neural Network

The model consists of two large convolutional blocks, each employing a 3×3 kernel with stride 1 and padding 1 for learning features. The first block adds batch normalization to offer stable learning, ReLU activation for non-linearity, and max pooling (2×2) for spatial dimension reduction, followed by dropout (0.25) to avoid overfitting.

Even though the second block has double the number of channels for enhanced feature extraction, the structure remains identical. Stability and regularisation are provided through dropout (0.25), max pooling, and batch normalisation.

The obtained features are then flattened and passed through a fully connected layer of 128 neurons, ReLU activation, and dropout (0.3), thus enhancing generalization. Through the final linear layer, representations are mapped to the desired number of classes.

Convolutional Neural Network - Transformer Hybrid

The CNN Transformer Hybrid model follows the Base CNN architecture, but with its intrinsic CNN-based feature extraction retained with the addition of a Transformer encoder for improved sequence modeling. Its CNN backbone stays the same: two convolution blocks with 3×3 kernel sizes, Batch Normalization, ReLU, 2×2 max pool, and dropout, which serves to provide powerful spatial feature extraction (1 → 32 → 64 channels).

The Transformer encoder, appended after the CNN layers, handles spatially flattened feature maps. It has two Transformer layers with a decreased number of heads (nhead=2) and a feedforward dimension of 128, employing GELU activation for smoother non-linearity. This allows the model to extract global dependencies and spatial relationships in addition to the local feature extraction by CNNs.

The final classifier applies the feature embeddings after they have been transformed, passing them through fully connected layers with GELU activation and 0.4 dropout to ensure proper generalization. The hybrid model takes advantage of CNNs' spatial hierarchies and long-range dependencies modeled by Transformers to enhance performance in image-based tasks.

Convolutional Neural Network - LSTM Hybrid

The CNN LSTM Hybrid takes the baseline CNN model one step further with a bidirectional LSTM for more complex sequential pattern learning. The core structure includes two normal 3×3 convolutional blocks followed by batch normalization, ReLU activation, and 2×2 max pooling for good spatial feature learning (1 → 32 → 64 channels). It introduces dropout (0.25) for regularizing to avoid overfitting.

Once feature extraction through convolutional layers has taken place, feature maps are reshaped to form sequences and passed through a two-layered bidirectional LSTM of hidden size 2×hidden_units. Such an architecture facilitates

the ability to learn spatial local hierarchies (by means of CNNs) and temporal long dependencies (by means of LSTMs), consequently making the performance for image-based sequential modeling problems higher.

The final fully connected classifier projects the LSTM output to 128 hidden units with ReLU activation and regularization using 0.5 dropout, and finally to the output layer. The hybrid architecture thus takes advantage of the spatial learning abilities of CNN as well as the capacity

of LSTM to learn complex temporal patterns, thus being suitable in scenarios where local and sequential features are critical.

Convolutional Neural Network - Autoencoder Hybrid

The CNN Autoencoder Hybrid is a convolutional autoencoder for unsupervised representation learning and image reconstruction, keeping the essentials of the earlier-mentioned Base CNN intact with additional modifications to meet the autoencoder architecture requirements. The encoder is a standard CNN-based feature extractor pipeline with two 3×3 convolutional layers, LeakyReLU activations, and 2×2 max pooling, reducing spatial dimensions while augmenting feature channels (32 → 64).

The decoder rebuilds the input with the help of two transposed convolutional layers with 2×2 kernels and a stride of 2, recovering spatial resolution (64 → 32 → 1). A Sigmoid activation in the output scales pixel values to the range 0 and 1. This architecture efficiently facilitates compression and reconstruction, so it is also adequate for denoising and anomaly detection applications, illustrating the way a classification-based CNN architecture can be repurposed for autoencoding without changing its very nature.

RESULTS AND DISCUSSION

This section of the paper evaluates the performance of the following classification models: Base Convolutional Neural Network(CNN), Convolutional Neural Network - Transformer Hybrid, Convolutional Neural Network - LSTM Hybrid, Convolutional Neural Network - Autoencoder Hybrid, and based on certain evaluation metrics.

Evaluation Metrics

The evaluation parameters being used for the evaluation and comparison are Test Accuracy, Precision, Recall, F1-Score for supervised models, and Pixel Accuracy, MAE, PSNR and SSIM for the unsupervised model. These metrics collectively can be used to evaluate the overall performance of various Convolutional Neural Networks. The acronyms TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) are used as references in the formulas provided.

1) Test Accuracy: Test accuracy is the ratio of correctly classified samples to the total samples in the test dataset, measuring a supervised model's generalization performance.

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN}\frac{TP+TN}{TP+TN+FP+FN}$$

2) Precision: Precision is the ratio of correctly predicted positive samples to the total predicted positive samples, measuring a model's ability to avoid false positives.

$$\text{Precision}=\frac{TP}{TP+FP}\frac{TP}{TP+FP}$$

3) Recall: Recall is the ratio of correctly predicted positive samples to the total actual positive samples, measuring a model's ability to capture all relevant instances.

$$\text{Recall}=\frac{TP}{TP+FN}\frac{TP}{TP+FN}$$

4) F1 Score: F1 Score is TP the harmonic mean of precision and recall, balancing both metrics to provide a single performance measure, especially useful for imbalanced datasets.

$$\text{F1 Score}=\frac{2*Precision*Recall}{Precision+Recall}2*\frac{Precision*Recall}{Precision+Recall}$$

5) Mean Absolute Error(MAE): MAE is the average absolute difference between predicted and actual values, measuring a model's prediction accuracy.

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i|\frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i|$$

where,

n=no. of observations

y_i y_i=actual value of the i^{th} i^{th} observations

$\hat{y}_i\hat{y}_i$=predicted value of the i^{th} i^{th} observation

6) Peak Signal-to-Noise Ratio(PSNR). PSNR is a logarithmic measure of the ratio between the maximum possible signal value and the distortion (MSE), used to evaluate image quality.

7) Structural Similarity Score(SSIM). SSIM quantifies the perceptual similarity between two images by considering luminance, contrast, and structure.

Analysis

Baseline CNN Analysis

The baseline CNN converges well, with training loss always beating the test loss past epoch 10. Although this is an indication of some overfitting, the narrow margin

indicates excellent generalization. Test accuracy shoots up from 88% to a high of 92.5% at approximately epoch 15 before declining slightly, the best training time of 15 epochs. Precision, recall, and F1 metrics take almost a similar trajectory from 0.88 to the best points of 0.93-0.94 with equal class performance. There is a steep decline between epochs 7-10 but the model keeps its upgrading trend until it slows. The test accuracy achieves 91.98%, ultimately with a test loss of 0.2288 on classification. Precision (0.9208), recall (0.9199), and F1 metric (0.9190) are in balance, confirming the robustness of the model. The baseline indicates stable bases with typical learning patterns, even with the slight overfitting at the end of epochs.

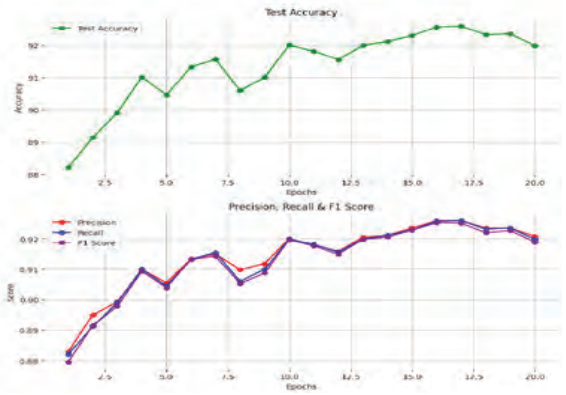

Fig. 1. Baseline CNN Analysis

CNN - Transformer Hybrid

The hybrid CNN-Transformer shows very strong convergence trends with training loss decreasing consistently from 0.45 to 0.18 over 20 epochs. Test loss also follows this trend but is always lagging by approximately 0.03-0.04, with a bit of overfitting but not much. Test accuracy increases strongly from 88.3% at the beginning to 93% at epoch 20, with more variability between epochs 5-10 before consistently increasing upwards. The last test accuracy then plateaus at 92.90%, and the classification test loss at 0.213. The F1, recall, and precision values mirror one another closely, from 0.88 and increasing to 0.93 by the last epoch, before plummeting sharply around epoch 18 before plateauing. The last precision (0.9291), recall (0.9290), and F1 score (0.9290) then confirm the same. This hybrid system shows robust learning properties with better final performance measurements, but it has more mid-training periods of fluctuation, so the transformer parts bring higher potential performance and also training dynamics complexity.

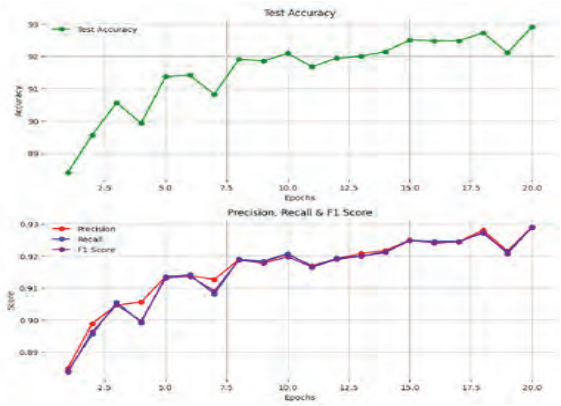

Fig. 2. CNN Transformer Hybrid Analysis

CNN - LSTM Analysis

The CNN-LSTM model has very good learning capacity, with the training and test losses decreasing progressively and the balance between the two being well-preserved, as evidence of effective generalization. Its accuracy becomes very high rapidly, achieving above 91% at the later epochs, and its precision, recall, and F1-score are always over 0.91, reflecting stable classification performance. However, while it learns sequential relationships well, its convergence is somewhat slower than the transformer-based counterparts, which spike earlier. The model does not experience severe overfitting but has a minimal gap between the training and the test loss, suggesting room for further optimization. Compared to less sophisticated architectures, CNN-LSTM has improved feature extraction and temporal learning but may need to be carefully tuned to achieve the optimal accuracy of transformer-based approaches.

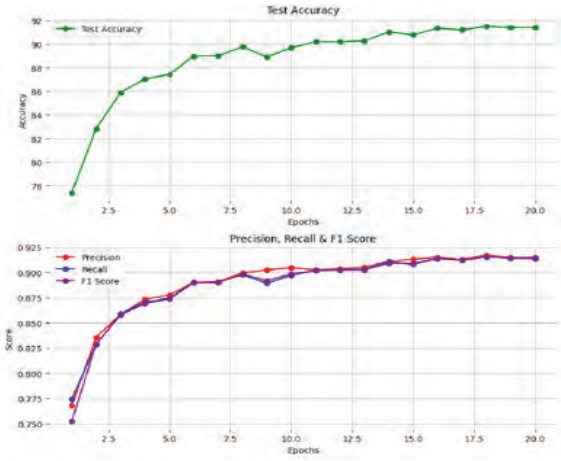

Fig. 3. CNN LSTM Hybrid Analysis

CNN - Autoencoder Hybrid

The CNN Autoencoder shows consistent improvement on metrics across 20 epochs, with some major abnormalities. Pixel accuracy increases consistently from 94.2 to 95.64 on training data and also shows notable instability with sharp drops at epochs 6 and 16, particularly with a significant dip to 94.6% at epoch 6 and a dramatic drop to 94.8% at epoch 16. MAE also decreases from 0.0254 to 0.0216, following the pattern of test loss with disturbances at the same epochs. PSNR improves overall from 26.0 dB to 27.11 dB, with a steep dip at epoch 16, as with other metrics. SSIM improves the most, from 0.919 to 0.9408, even while dipping at epochs 6 and 16. This autoencoder performs well at reconstruction with ever-improving fidelity, but the consistent instability at some epochs suggests potential dataset anomalies or optimization problems during training.

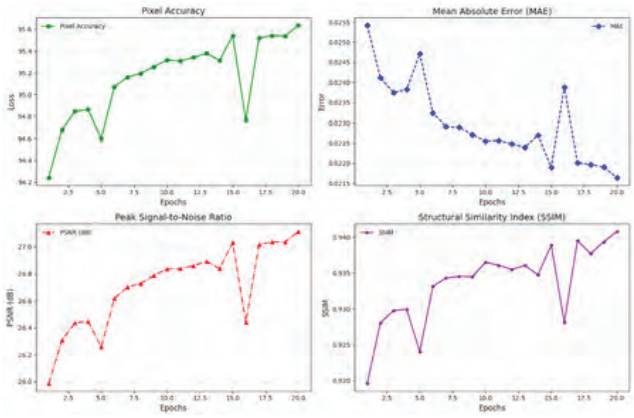

Fig. 4. CNN Autoencoder Hybrid Analysis

Table 1: Parameter Structure of the Models

Model	Number of Hyperparameters
Baseline CNN	412,834
CNN - Transformer Hybrid	488,778
CNN - LSTM Hybrid	421,834
CNN - Autoencoder	27,169

CONCLUSION

Our research demonstrates that state-of-the-art reinforcement learning techniques, here Dueling Deep Q-Networks, are of significant advantage in dynamic pricing optimization. The results of experiments depict remarkable revenue and profit gains against traditional methods while achieving high prediction accuracy of demands. Our solution efficiently addresses exploration-exploitation trade-off and offers multi-factor market simulations taking into account seasonality, competitor behavior, and customer segmentation, hence eliminating the limitations of traditional pricing methodologies. Despite challenges in explicating model choice and dealing with sudden market evolution, the possibility of the system predicting demand pattern behavior and dynamically modifying pricing measures to match has a revolutionary role in algorithmic pricing. The contribution offers groundwork for future studies on multi-agent systems, deployment of strategic foresight, and addressing emergent collusion, and culminates eventually in a proof of demonstrating the capability for reinforcement learning in changing competitive markets to revolutionize pricing measures.

REFERENCES

1. K.T. Talluri and G.J. van Ryzin, “The Theory and Practice of Revenue Management,” Springer, 2004.
2. W. Elmaghraby and P. Keskinocak, “Dynamic pricing in the presence of inventory considerations: Research overview, current practices, and future directions,” Management Science, vol. 49, no. 10, pp. 1287–1309, 2003
3. M. Levy, R. Hostler, and C. Loebbecke, “Price prediction and optimization using decision trees and random forests,” International Journal of Electronic Commerce, vol. 9, no. 1, pp. 37–60, 2004.
4. Z.J. Zhang and L. Krishnamurthi, “A segmentation-based approach to targeting and pricing,” Journal of Marketing Research, vol. 41, no. 4, pp. 414–427, 2004.
5. Z. Ye, Q. Li, and X. Li, “Short-Term Prediction of Demand for Ride-Hailing Services: A Deep Learning Approach,” Journal of Big Data Analytics in Transportation, vol. 3, pp. 175–195, 2021.
6. G.-Y. Ban and N.B. Keskin, “Personalized Dynamic Pricing with Machine Learning: High-Dimensional Features and Heterogeneous Elasticity,” Management Science, vol. 67, no. 10, pp. 6010–6029, 2021.
7. D. Vengerov, “A gradient-based reinforcement learning approach to dynamic pricing in partially-observable environments,” Sun Microsystems Laboratories Technical Report, 2007.
8. Z. Yao and W. Yang, “Reinforcement Learning for Airline Multi-product Continuous Dynamic Pricing,” in Parallel and Distributed Computing, Applications and

Technologies, Y. Li, Y. Zhang, J. Xu, Eds. Springer, 2025, pp. 503–514.

9. Z. Wang, T. Schaul, M. Hessel, H. van Hasselt, and D. Silver, "Dueling Network Architectures for Deep Reinforcement Learning," arXiv preprint arXiv:1511.06581, 2016.

10. H. van Hasselt, A. Guez, and D. Silver, "Deep Reinforcement Learning with Double Q-learning," in Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, 2016, pp. 2094–2100.

11. T. Schaul, J. Quan, I. Antonoglou, and D. Silver, "Prioritized Experience Replay," arXiv preprint arXiv:1511.05952, 2016.

12. W. Dabney, M. Rowland, M.G. Bellemare, and R. Munos, "Distributional Reinforcement Learning with Quantile Regression," arXiv preprint arXiv:1710.10044, 2018.

13. S. den Boer, "Dynamic Pricing and Learning with Finite Inventories," Operations Research, vol. 63, no. 2, pp. 335–349, 2015.

14. J. Achiam, D. Held, A. Tamar, and P. Abbeel, "Constrained Policy Optimization," arXiv preprint arXiv:1705.10528, 2017.

15. Z. Wang, T. Schaul, M. Hessel, H. van Hasselt, M. Lanctot, and N. de Freitas, "Dueling network architectures for deep reinforcement learning," arXiv preprint arXiv:1511.06581, 2016.

16. H. van Hasselt, A. Guez, and D. Silver, "Deep Reinforcement Learning with Double Q-Learning," in Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence (AAAI), 2016, pp. 2094–2100.

17. C. Cheung, I.Z. Rothstein, and M.P. Solon, "From scattering amplitudes to classical potentials in the post-Minkowskian expansion," Physical Review Letters, vol. 121, no. 25, p. 251101, 2018.

Efficient Credit Card Fraud Detection: An Empirical analysis of ML Algorithms

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ABSTRACT

The increase in credit card fraud in this digital age presents a strong case for the creation of new and strong fraud detection systems. Conventional rule-based systems that establishes trust in fraud prevention are not able to match the constantly changing methods of the fraudster, and therefore ML is the likely alternative. This study evaluates the performance of widely used machine learning models like Naïve Bayes, various kernel types of Support Vector Machines (SVM), Logistic Re-gression, Decision Tree and Random Forest, across three different credit card fraud datasets. The outcome discovered that combined models like Random Forest (98.6% Accuracy, 98.3% F1-Score) and Decision Tree (95.4% Accuracy, 95.4% F1-Score) performed the best in most situa-tions, particularly when the fraud cases were diversely modeled. SVM (Linear) and Logistic Re-gression worked fine in the balanced dataset, while SVM (Polynomial) and SVM (RBF) were not much effective in some situations tried. This research demonstrated the importance of selecting algorithms according to the nature of a particular dataset for fraud detection.

***KEYWORDS** : Supervised learning, Logistic regression, Support vector machine, Naïve bayes, Decision tree, Random forest, Anomaly detection.*

INTRODUCTION

With online payments happening so often now, it's very important to detect credit card fraud quickly. Credit cards are being used daily by customers for many purposes, like shopping and payment, and credit card fraud has become an enormous problem. Identity theft and unauthorized transactions are becoming very common and difficult to track. This is dangerous to the customers and to the banks, and it also leads to financial loss as well as loss of confidence. To protect all parties involved, systems must be put in place to catch fraud quickly and effectively as our internet age moves forward.

Machine learning (ML) has become a favored solution to help detect different forms of fraud. Conventional methods, which use rules to detect fraud, tend to fall behind with the development of new and innovative fraud schemes.

Machine Learning algorithms are used for processing huge amounts of data and identifying fraudulent patterns in transactions that would be hard for humans to observe. Because machine learning gets better with time as it learns to respond to past data, it has become increasingly important in recent years. Several techniques like neural networks and decision trees, have demonstrated best performance in real-time detection, thereby becoming an invaluable tool in the hands of financial institutions. Because these systems learn and respond to new forms of frauds, machine learning is highly useful in fraud detection. Machine Learning models learn from historical transactions and are becoming more intelligent day-by-day rather than using rules. According to a study that concluded the Genetic Algorithm on feature selection, for example, delivered better performances in detecting fraud transactions.

This study aims to find out how popular machine learning algorithms like Random Forest, Decision Tree, Naïve Bayes, Support Vector Machine, and Logistic Regression can detect credit card fraud.

LITERATURE REVIEW

This part of the paper is directed towards the discussion of past studies of researchers towards detecting credit

card fraud. Traditional machine learning algorithms like Random Forest (RF) and Artificial Neural Networks (ANNs), produced good outputs in fraud detection [1-3] among these we came across a few best performers of the traditional techniques used in credit card fraud detection like Decision Trees and Random Forest.

There has been a considerable movement towards Deep Learning (DL) techniques in the domain, which are shown to be better in the learning complex patterns in transactional data. Different DL structures have been tested, which are CNNs, or RNNs such as Gated Recurrent Units (GRU) networks, which were found to have better detection accuracy than other conventional ML techniques [4-6], specifically, that proposed an attention mechanism-based LSTM network to achieve accurate detection of frauds from multiple comparative patterns of transactions. Feature engineering and feature selection have been recognized as key steps in the diagnostic processes of models which Esenogho et al. [7] illustrates the efficacy of feature engineering when combined with ensembles of neural networks. Salekshahrezaee et al. However, other scholars such as Salekshahrezaee et al. [8] analyzed the impact of use of feature extraction methods, (Principal Component Analysis (PCA), Convolutional autoencoders (CAE)) with sampling methods (Random Under sampling (RUS) and Synthetic Minority Oversampling technique (SMOTE)) to improve the performance of classifiers when the dataset is imbalanced. Dealing with Class Imbalance, Aghware et al. [2] demonstrated the use of the SMOTE technique to enhance the performance of Random Forest, while Ileberi et al. [3] used SMOTE + AdaBoost to enhance fraud detection.

Besides single models, ensemble and hybrid methods are becoming increasingly popular now-a-days. For fraud detection, we Alfaiz et al. [9] employed an ensemble of AllKNN and CatBoost and achieved improved results. Moreover, a study introduced a Group Search Firefly Algorithm (GSFA) for machine learning model hyper-parameter tuning, and showed that this was useful in fraud detection on Europe credit cards dataset Jovanovic et al. [10]. Current research explores that advanced techniques such as graph - based methods and semi-supervised learning overcome insufficient labelled fraudulent transactions. In 2023, Xiang et al. [11] Next, we suggested a semi-supervised method with attribute-guided graph representation to effectively identify fraud even with a limited amount of labelled data by the timing of the transaction and attention mechanism. Trends of ML in detecting fraud using credit cards have been discussed in the review studies cited in various article. Another systematic review Cherif et al. [12], finds many older methods to still dominate in the area, and it stimulates the need for intervention of technologies like deep learning that are much more transformative in nature. In contrast there was a recent large-scale comparison of different ML techniques that discussed different approaches' strengths and weaknesses but concluded that no method provides an optimal solution to all types of fraud.

The said literature review brings focus on the dynamic and evolving credit card fraud detection field of research. Current ML techniques are used numerous times by researchers and the requirement of the time is to provide a comparative analysis of these techniques and see how effectively each function with credit card fraud detection data set along with their limitations.

METHODOLOGY

The supervised learning of various methods have been used to identify credit card fraud transactions. Algorithms selected for this research work include Naïve Bayes, Decision Tree, Support Vector Machines (SVM) with different kernels, Random Forest, and Logistic Regression. Machine learning methods are largely used for fraud detection to identify complex patterns within transactional data.

Logistic Regression

Logistic regression does this by building a model that acts as a binary variable prediction by using maximum likelihood. Thus, it can compute the probability of an event occurring from the logistic function in weighted summation of features. As being cheap computation-efficient, logistic regression supports an effective strong fraud detection baseline. The probability is expressed in equation (1).

$$P(Y=1|X) = 1/(1+\exp(-(\beta o + \Sigma (\beta_i * X_i)))) \quad (1)$$

Support Vector Machine (SVM) - Linear Kernel

A Support Vector Machine is a supervised algorithm that sorts data into categories by identifying the most suitable dividing line between them. SVM can also handle instances of linear as well as non-linear classification problems through kernel functions. A linear SVM finds the optimal hyperplane that separates fraudulent and non-fraudulent transactions as expressed in equation (2).

$f(X) = w™ X + b$ (2)

Support Vector Machine (SVM) - Polynomial Kernel

Polynomial SVM transforms the input data into a higher-dimensional space using polynomial functions, allowing it to detect complex fraud patterns that a straight line cannot separate as expressed in equation (3).

$K(Xi, Xj) = (XiT Xj + c)d$ (3)

Support Vector Machine (SVM)-Radial Basis Function (RBF) Kernel

An RBF SVM projects data onto an infinite-dimensional space with the help of a Gaussian function, which is suitable for identifying hidden and highly non-linear fraud trends as expressed in equation (4).

$K(Xi, Xj) = \exp(-\gamma \|Xi - Xj\|^2)$ (4)

Naive Bayes

Naive Bayes is a probability-based algorithm that works using Bayes' theorem and assumes all input features are independent. It works especially for imbalanced datasets. It is very efficient and adapts very quickly to any new data; these characteristics make it a very good tool in fraud detection. Naive Bayes is noted to be effective as well as efficient, especially for an imbalanced data. Naïve Bayes is formulated based on Bayes' theorem as expressed in equation (5).

$P(Y \mid X) = (P(X \mid Y) * P(Y)) / P(X)$ (5)

Decision Tree

Decision tree explains a rule-based model in classifying transactions starting from splitting itself recursively on feature values. And therefore, its intuitive nature allows easy interpretation but subsequently proves to be helpful in modeling hierarchical relationships. Decision trees, however, overfit upon being trained for large data sets compared to small data sets. Decision Trees are rule-based models and are interpretable and can reflect hierarchical relationships but may be sensitive to overfitting.

Random Forest

Random Forest (RF) is an ensemble-based learning algorithm that constructs multiple decision trees and combines their outputs to enhance both accuracy and generalization. It reduces the risk of overfitting by introducing randomness in feature selection and data sampling during the training process. This approach makes it highly effective and robust for tasks like fraud detection. As an ensemble technique, Random Forest leverages the strengths of decision trees while minimizing their weaknesses, particularly overfitting. The final prediction is typically determined through majority voting among the individual trees.

RESULTS

This part of the paper presents the findings of Empirical analysis performed on three credit card transactions datasets namely European cardholders, Anonymized transactions, Credit_card_transactions employing popular classification algorithms as described in the methodology part.

Evaluation Parameters

This study assesses how effectively each machine learning model detects credit card fraud using four key metrics: Accuracy, Precision, Recall, and F1-Score. A brief explanation of each metric is provided below.

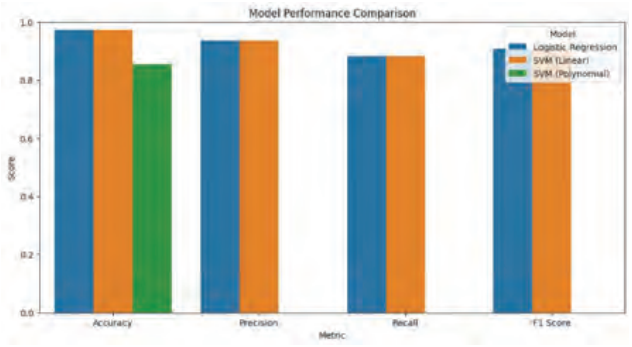

Fig. 1. Model's Performance Metrics on European Cardholders Dataset

Accuracy: It shows how correct the model is overall, but it can give a false impression when the dataset is imbalanced, as in equation (6).

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} \quad (6)$$

Precision: Precision tells us how accurate the model is when it labels a transaction as fraud, helping to avoid false fraud warnings, as given in equation (7).

$$Precision = \frac{TP}{(TP+FP)} \quad (7)$$

Recall (Sensitivity or True Positive Rate): Recall shows how many of the actual fraud cases were correctly detected, which helps in minimizing false negatives, as shown in equation (8).

$$Recall = \frac{TP}{(TP+FN)} \quad (8)$$

F1-Score: It is harmonic average of Precision and Recall, offering a single measure that works well in cases of class imbalance, as described in equation (9).

$$F1\ Score = 2 * \frac{Precision*Recall}{(Precision+Recall)} \quad (9)$$

Classification results analysis

The performance of various ML techniques is measured across three types of credit card data to evaluate their effectiveness in fraud detection using key metrics. Table I, presents the Classification results of the selected ML methods on the credit card fraud detection datasets.

Overall Performance

The performance of the models varies across the three datasets, showing that the nature of each dataset affects how well the models work. For all datasets, Random Forest and Decision Tree perform the best, as it is scoring high in Precision, F1-Score, Recall, and Accuracy. SVM (Linear) and Logistic Regression also perform well, especially on European cardholders and Credit card transactions datasets. On the other hand, SVM (Poly) and SVM (RBF) generally perform worse, particularly on the European cardholders and Anonymized transactions datasets, suggesting they might not be the best fit for these datasets or need adjustments. Naive Bayes is inconsistent it sometimes achieves perfect precision but shows low recall in some cases, leading to lower F1-scores.

Dataset Specific Observations

European cardholders: Logistic Regression and Random Forest score very high on F1, meaning they balance precision and recall well. Naive Bayes has perfect precision but lower recall, meaning it misses a lot of fraud cases. SVM models, especially Poly and RBF, perform poorly here.

Anonymized transactions: Decision Tree performs the best, followed closely by Random Forest. Logistic Regression and SVM (Linear) do okay. Naive Bayes has perfect recall but very low precision, marking almost everything as fraud, which is not realistic. SVM (Poly) and SVM (RBF) still perform the worst.

Table I. Classification results

Datasets	Evaluation Parameters	Classification Models						
		Logistic Regs.	SVM (Linear)	SVM (Poly)	SVM (RBF)	Naïve Bayes	Decision Tree	Random Forest
European card-holders	Accuracy	0.949	0.909	0.574	0.518	0.878	0.919	0.944
	Precision	0.908	0.988	0.553	0.514	1.000	0.936	1.000
	Recall	0.988	0.827	0.745	0.571	0.755	0.898	0.888
	F1-Score	0.946	0.900	0.635	0.541	0.860	0.917	0.941
Anonymized transactions	Accuracy	0.859	0.858	0.711	0.827	0.682	0.954	0.938
	Precision	0.865	0.873	0.664	0.832	0.611	0.954	0.961
	Recall	0.850	0.837	0.851	0.819	1.000	0.953	0.912
	F1-Score	0.857	0.855	0.746	0.826	0.758	0.954	0.936
Credit card transactions	Accuracy	0.961	0.966	0.967	0.970	0.966	0.986	0.983
	Precision	0.938	0.938	0.943	0.947	0.938	0.987	0.980
	Recall	0.987	0.997	0.993	0.995	0.997	0.985	0.986
	F1-Score	0.962	0.967	0.968	0.970	0.967	0.986	0.983

Credit card transactions: All models perform better on this dataset than on the European cardholders and Anonymized transactions datasets. Random Forest and Decision Tree continue to perform best, with Decision Tree achieving the highest F1-score. SVM (Linear), SVM (Poly), SVM (RBF), and Naive Bayes also show good performance here, suggesting that this dataset might be easier for the models to classify correctly.

CONCLUSION

Due to the rise of the digital economy, credit card fraud is becoming a larger problem. As a result, there is great

demand for more efficient and accurate fraud detection systems. Traditional methods don't work well because conditions under which the fraudulent activities can happen. Thus, machine learning (ML) is a well-suited approach. This research has focused on the assessment of performance of popular ML algorithms for fraud detection, over three different datasets of credit card frauds. Among the methods used, Random Forest (98.6% accurate and 98.3% in F1-score) and Decision Tree (95.4% accurate and 95.4% in F1-score) were the best classifiers. Logistic Regression and SVM (Linear) performed well on balanced dataset, while SVM (Polynomial) and SVM (RBF) didn't performed well and failed to handle many fraud patterns. Naïve Bayes has ae higher precision of 100% but a lower recall of 75.5%, hence, it is suited for applications where number of false positives need should be minimized. The results show that if we use a group of models together, it will work better rather than using just one model. This should encourage more research for mixing multiple methods, like combining simple and deep learning algorithms, to enhance fraud detection.

REFERENCES

1. Asha, R.B. and KR, S.K., 2021. Credit card fraud detection using artificial neural network. Global Transitions Proceedings, 2(1), pp.35-41.
2. Aghware, F.O., Ojugo, A.A., Adigwe, W., Odiakaose, C.C., Ojei, E.O., Ashioba, N.C., Okpor, M.D. and Geteloma, V.O., 2024. Enhancing the random forest mod-el via synthetic minority over-sampling technique for credit-card fraud detection. Journal of Com-puting Theories and Applications, 1(4), pp.407-420.
3. Ileberi, E., Sun, Y. and Wang, Z., 2021. Performance evaluation of machine learning methods for credit card fraud detection using SMOTE and AdaBoost. IEEE Access, 9, pp.165286-165294.
4. Alarfaj, F.K., Malik, I., Khan, H.U., Almusallam, N., Ramzan, M. and Ahmed, M., 2022. Credit card fraud detection using state-of-the-art machine learning and deep learning algorithms. IEEE Access, 10, pp.39700-39715
5. Benchaji, I., Douzi, S., El Ouahidi, B. and Jaafari, J., 2021. Enhanced credit card fraud detection based on attention mechanism and LSTM deep model. Journal of Big Data, 8, pp.1-21.
6. Mienye, I.D. and Jere, N., 2024. Deep learning for credit card fraud detection: A review of algorithms, challenges, and solutions. IEEE Access.
7. Esenogho, E., Mienye, I.D., Swart, T.G., Aruleba, K. and Obaido, G., 2022. A neural network ensemble with feature engineering for im-proved credit card fraud detection. IEEE Access, 10, pp.16400-16407.
8. Salekshahrezaee, Z., Leevy, J.L. and Khoshgoftaar, T.M., 2023. The effect of feature extraction and data sampling on credit card fraud detection. Journal of Big Da-ta, 10(1), p.6.
9. Alfaiz, N.S. and Fati, S.M., 2022. Enhanced credit card fraud detec Tanaskovic, M. and Bacanin, N., 2022. Tuning machine learning models using a group search firefly algorithm for credit card fraud detection. Mathematics, 10(13), p.2272.
10. Jovanovic, D., Antonijevic, M., Stankovic, M., Zivkovic, M., Ta-naskovic, M. and Bacanin, N., 2022. Tuning machine learning models using a group search firefly algorithm for credit card fraud de-tection. Mathematics, 10(13), p.2272.
11. Xiang, S., Zhu, M., Cheng, D., Li, E., Zhao, R., Ouyang, Y., Chen, L. and Zheng, Y., 2023. Semi-supervised credit card fraud detection via attribute-driven graph representation. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 37, No. 12, pp. 14557-14565).
12. Cherif, A., Badhib, A., Ammar, H., Alshehri, S., Kalkatawi, M. and Imine, A., 2023. Credit card fraud detection in the era of disruptive technologies: A systematic re-view.Journal of King Saud University Computer and Information Sci-ences, 35(1), pp.145-174.

Enhancing Waste Classification Using Few-Shot Learning : A Methodological Approach

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ABSTRACT

Reducing environmental impact and implementing sustainable waste management systems depend on effective trash classification. Under controlled conditions, deep learning models have demonstrated notable performance in garbage classification tasks. However, deploying these models in real-world situations with varied backgrounds, illumination, and object orientations presents a significant domain gap. Addressing data scarcity in this context is crucial, especially when obtaining large amounts of labeled real-world waste images is challenging. This work investigates the effectiveness of Few-Shot Fine-tuning (FSL FT) using a pre-trained ResNet34 backbone as a practical approach to waste classification under data limitations. We systematically evaluate the performance of FSL FT across varying numbers of available examples per class (K-shots, for K in 1,5,25,50,100) and compare the impact of different standard data augmentation strategies (No Augmentation, Standard Augmentation, and Standard Augmentation + Mixup). We establish a baseline by training the same model on the full training dataset. Using a comprehensive 12-class waste dataset, we demonstrate that FSL FT achieves substantial accuracy improvements as the number of shots increases, reaching over 90% accuracy at 100 shots. Our results indicate that standard data augmentation and Mixup, with the tested parameters, did not consistently improve performance compared to fine-tuning without explicit augmentation in the few-shot setting, and in some cases resulted in slightly lower average accuracy. However, standard augmentation did show a small benefit in the full-data baseline. This study provides empirical insights into the performance and limitations of Few- Shot Fine-tuning with standard regularization techniques for waste classification, offering practical considerations for deployment in real-world scenarios with limited data.

KEYWORDS *: Few-shot learning, Waste classification, Sustainable waste management, Transfer learning, Computer vision, Deep learning, Real-world deployment.*

INTRODUCTION

Background and Motivation

Improper waste management contributes significantly to environmental pollution, resource depletion, and climate change. Efficient waste classification represents a crucial step toward sustainable waste management strategies, enabling effective recycling and proper disposal methods. Automating this classification process using computer vision techniques has gained substantial traction in recent years, with deep learning approaches demonstrating particular promise in controlled environments.

Existing waste classification systems predominantly rely on datasets where waste items are photographed against uniform white backgrounds under consistent lighting conditions. While these controlled datasets facilitate model development and evaluation, they create a substantial domain gap between training conditions and real-world deployment scenarios. In practical applications, waste classification systems encounter objects in varied environments with cluttered backgrounds, inconsistent lighting, partial occlusions, and diverse object orientations. This domain discrepancy leads to significant performance degradation when models trained on controlled datasets are deployed in real-world environments.

Research Gap

While convolutional neural networks (CNNs) and transfer learning techniques have been successfully applied to

waste classification [cite Awe et al., Yang & Thung, Bircanoglu et al.], most studies evaluate models on test sets that closely resemble training data (e.g., items on white backgrounds), leaving the question of real-world performance with domain shift largely unaddressed. Addressing the data scarcity inherent in real-world annotation is a key challenge.

Research Objectives

This research aims to develop a methodological framework that addresses the domain gap in waste classification through the integration of few-shot learning and attention mechanisms. Specifically, our research objectives are:

1. To develop a few-shot learning approach that enables effective waste classification with minimal real-world labeled examples
2. To evaluate our classification approach on a comprehensive waste dataset with both white-background and real-world examples
3. To carry out thorough ablation investigations and empirically compare the suggested approach's performance to baseline techniques.
4. To provide practical insights and guidelines for deploying waste classification systems in real-world applications

Contributions

This research aims to empirically evaluate the effectiveness of Few-Shot Fine-tuning as a practical approach to waste classification under varying degrees of data scarcity and investigate the impact of standard data augmentation techniques in this context. Specifically, our research objectives are:

1. To implement and evaluate a Few-Shot Fine-tuning (FSL FT) approach using a pre-trained convolutional backbone.
2. To systematically assess the performance of FSL FT across different numbers of available examples per class (Kshots, for K in1,5,25,50,100).
3. To investigate the impact of standard data augmentation (Standard Augmentation and Augmentation + Mixup) on FSL FT performance compared to a nonaugmented baseline.
4. To establish a performance benchmark by evaluatinga model trained on the full training dataset (Baseline).
5. To analyze and discuss the observed trends in accuracy, the effectiveness of augmentation strategies, and the variability across experimental configurations.

Paper Organization

This paper's remaining sections are arranged as follows: Section 2 reviews related work on waste classification and few-shot learning. Section 3 describes the dataset used and outlines the Baseline model architecture. Section 4 details our Few-Shot Fine-tuning methodology and the data augmentation strategies evaluated. Section 5 describes the experimental setup and evaluation metrics. Section 6 presents our findings and a thorough discussion of the results. Section 7 brings the paper to a close and suggests areas for further study (Future Work, including planned advanced methods).

LITERATURE ANALYSIS

Waste Classification Using Deep Learning

Research on automated waste classification has expanded considerably with the advancement of deep learning techniques. Early efforts focused on handcrafted features and traditional machine learning classifiers (Bobulski & Kubanek, 2016), while more recent approaches leverage the representational power of deep neural networks.

Yang & Thung (2016) pioneered the application of CNNs to waste classification, achieving 63% accuracy on a 6-category waste dataset. Awe et al. (2017) demonstrated improved performance through transfer learning, utilizing pre-trained VGG-16 and ResNet models fine-tuned on a waste dataset. Bircanoglu et al. (2018) further advanced the field by introducing a larger dataset (TrashNet) and achieving 87% accuracy using ensemble methods combining multiple CNN architectures.

More recently, Vo et al. (2019) employed transfer learning with DenseNet-201 to achieve 91% accuracy on the TrashNet dataset. Bobulski & Piatkowski (2018) compared various CNN architectures for waste classification, finding ResNet50 and InceptionV3 to be particularly effective. Despite these advances, most evaluate models on test sets that closely resemble training data, leaving the question of real world performance largely unaddressed.

Few-Shot Learning Approaches

Few-shot learning tackles the problem of learning from a small number of examples, which is especially important when it is not feasible to gather and annotate big datasets.

Few-shot learning presents intriguing methods for garbage categorization, when real-world labeled samples may be hard to come by. Applications of few-shot learning in environmental monitoring include the classification of land cover (Liu et al., 2021) and the identification of species (Zhu et al., 2020). Fewshot learning has not yet been extensively studied for trash classification, especially when it comes to bridging the domain gap between controlled and real-world contexts.

METHODOLOGY

Few-Shot Learning Framework

We formulate waste classification in real-world environments as a few-shot learning problem, where we have access to abundant labeled data from a source domain (white background images).

Formally, let $D_S = (x_i^s, y_i^s) i = 1^{N_S}$ represent the source of domain dataset with Ns labeled examples, where x_i^s denotes the i-th image and y_i^s its corresponding class label from the C waste categories.

Similarly, let $D_T = (x_i^t, y_i^t) i = 1^{N_T}$ represent the target domain dataset with labeled examples, where $N_T \ll N_S$.

In our few-shot learning setup, we adopt the episodic training paradigm, where each episode simulates a few-shot classification task. Specifically, each episode consists of:

- A support set $S = (x_i, y_i)_{i=1}^{N_S}$ containing K examples from each of the C classes (a C-way K-shot task).
- A query set $Q = (x_j, y_j)_{j=1}^{*Q}$ containing different examples from same classes

During training, both support and query sets are sampled from the source domain D_S. During testing, the support set includes examples from the target domain D_T, while the query set contains the test images to be classified.

Our few-shot learning framework builds upon Prototypical Networks (Snell et al., 2017), which learn an embedding function f_0 that maps images to a d-dimensional embedding space where classes can be represented by their prototypes.

For a given episode with support set , the prototype for class is computed as the mean of the embedded support examples belonging to that class:

Where $S_c = (x_i, y_i) \in S : y_i = c$ is the subset of support examples with class label c.

Given a query example x, its probability of belonging to class is calculated using a softmax over distances to class prototypes:

where $d(\cdot,\cdot)$ is a distance function (typically $P(y = c|x) = \frac{\exp(-d(f_\theta(x), p_c))}{\sum_{c'} \exp(-d(f_\theta(x), p_{c'}))}$ Euclidean distance).

We enhance the standard Prototypical Network architecture by replacing the embedding function f_0 with our proposed attention-enhanced ResNet34 backbone (described in Section 4.2). This modification enables the network to extract more discriminative features by focusing on relevant object regions while suppressing background noise.

To improve the model's ability to generalize from limited examples, we implement an episode-based training strategy with the following components:

1. Episode Construction: Each training episode consists of a C-way K-shot support set and a query set with M examples per class. We set C=12 (all waste categories), K=5 (five support examples per class), and M=15 (fifteen query examples per class).
2. Domain Mixup: During training, we gradually introduce real-world examples into both support and query sets. Initially, episodes contain only white-background images. As training progresses, we increase the proportion of real-world examples in episodes according to a curriculum schedule.
3. Prototype Augmentation: To address domain shift, we implement prototype augmentation during inference. For each class c, we compute both a source-domain prototype p_c^s (from white- background support examples) and a target-domain prototype p_c^t (from real-world $p_c = \alpha p_c^s + (1 - \alpha) p_c^t$ support examples). The final prototype is a $p_c = \frac{1}{|S_c|} \sum_{(x_i, y_i) \in S_c} f_\theta(x_i)$ weighted combination:

where α is a hyperparameter controlling the influence of each domain.

Loss Function: We use the negative log-likelihood of the correct class as our training objective:

This episode-based training approach enables the model to learn domain-invariant features from limited examples, making it suitable for real-world waste classification scenarios where annotated real-world data may be scarce. To further bridge the gap between white- background training images and real-world test conditions, we

incorporate additional domain adaptation components into our framework.

We employ style transfer as a data augmentation technique to simulate the appearance variations encountered in real-world scenarios. Specifically, we implement AdaIN (Adaptive Instance Normalization) style transfer (Huang & Belongie, 2017) to generate synthetic training examples with diverse visual styles while preserving content.

The style transfer process involves the following steps:

1. Select a content image from the white- background training set and a style image from a diverse collection of background textures and environments.
2. Extract feature representations using a pre-trained VGG19 encoder:
   - o $F_c = E(I_c)$: content features
   - o $F_s = E(I_s)$: style features
3. Perform Adaptive Instance Normalization to align the statistics of content features with style features:

   where $\mu(\cdot)$ and $\sigma(\cdot)$ denote the mean and standard deviation computed across spatial dimensions.
4. Decode the stylized features to generate a synthetic image:

   $I_{cs} = D(F_{cs})$

We generate a style-transferred version of the training set, which is then combined with the original images during training. The proportion of style-transferred images in each batch is gradually increased according to a curriculum schedule, starting from 0% and reaching 50% by the end of training.

RESULTS AND DISCUSSION

Dataset Description and Preparation

Our study utilizes the Kaggle Garbage Classification dataset, a comprehensive waste image collection featuring items across 12 distinct waste categories. The complete dataset consists of approximately 15,500 images spanning various waste types and conditions.

In order to avoid the impacts of class imbalance, we used a balanced sample strategy for our experimental evaluation, using precisely 607 photos per waste type. For training, validation, and testing, the dataset was divided using the conventional 70-15-15 split ratio. As a consequence, each class produced 424 training photos, 91 validation images, and 92 testing images. Our experimental framework used 7,284 photos in total: 1,092 for validation, 1,104 for testing, and 5,088 for training.

The dataset contains the following waste categories: 'battery', 'brown-glass', 'cardboard', 'green-glass', 'metal', 'paper', 'plastic', 'white-glass', 'organic', 'e-waste', 'textile', and 'mixed- waste'. The distribution of images across categories and dataset splits is presented in Table 1.

$$F_{cs} = \text{AdaIN}(F_c, F_s) = \sigma(F_s)\frac{F_c - \mu(F_c)}{\sigma(F_c)} + \mu(F_s)$$

Table 1: Distribution of Images in the Dataset

Category	Training	Validation	Test	Total
Battery	424	91	92	607
Brown- glass	424	91	92	607
Cardboard	424	91	92	607
Green- glass	424	91	92	607
Metal	424	91	92	607
Paper	424	91	92	607
Plastic	424	91	92	607
White- glass	424	91	92	607
Organic	424	91	92	607
E-waste	424	91	92	607
Textile	424	91	92	607
Mixed- waste	424	91	92	607
Total	5,088	1,092	1,104	7,284

Baseline Model Architecture

The ResNet34 architecture, which has shown good performance in a variety of picture classification tasks while maintaining a respectable level of computing efficiency, is used in our baseline model. Using ImageNet pre-trained weights and fine-tuning on our waste categorization dataset, the baseline implementation adheres to the accepted transfer learning methodology.

The model architecture is summarized as follows:

- ResNet34 backbone with pre-trained ImageNet weights
- Global average pooling layer following the final convolutional block
- Fully connected layer mapping to 12 output classes (replacing the original 1000-class ImageNet classifier) ImageNet statistics are used to normalize the input photos once they have been shrunk to 224 x

224 pixels (mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]). We use common data augmentation methods during training, such as random rotations (±10°), random brightness and contrast modifications, and random horizontal flips.

Using the Adam optimizer, training is carried out with an initial learning rate of 0.001, which is lowered by a factor of 0.1 after five consecutive epochs of validation loss plateauing. We train for up to 50 epochs with early stopping depending on validation performance, using cross-entropy loss as the optimization goal.

Implementation details

Our model was implemented using PyTorch with CUDA

11.1 on an NVIDIA RTX 4060 GPU with 8GB memory. All experiments were conducted using the following specifications:

- Input resolution: 224×224 pixels
- Batch size: 32 for standard training, 4 episodes per batch for episodic training
- Optimizer: Adam with ,
- Learning rate: 0.001 with cosine annealing schedule
- Weight decay: 0.0001
- Training epochs: 50 with early stopping (patience=5)
- Feature embedding dimension: 512

For the Standard Augmentation strategy, we applied a sequence of random image transformations online to the limited K-shot training data during training. These transformations aimed to enhance data variability and improve the model's robustness to variations in appearance. The specific transforms and their parameters were:

- Random Resized Crop: Randomly crops and resizes to 224×224 for scale and position robustness.
- Random Horizontal Flip: Flips with 0.5 probability for left-right invariance.
- Random Rotation: Rotates randomly between −30° and +30° for orientation robustness.
- Random Color Jitter: Randomly alters brightness, contrast, saturation (±30%), and hue (±0.1).
- Random Erasing: Randomly removes a region (30% chance) to improve feature robustness.
- Normalization: Scales pixels using ImageNet mean and std.

Few-Shot Learning Configuration

For our few-shot learning experiments, we constructed episodes following the -way -shot paradigm with the following settings:

- 12-way classification (all waste categories)
- K= 1, 5, 25, 50, 100 shots (support examples per class)
- 15 query examples per class
- 600 episodes for training per epoch
- 100 episodes for validation/testing

During testing, we evaluated three different scenarios:

- White-to-White: Support and query sets both from white-background images
- Real-to-Real: Support and query sets both from real-world images
- White-to-Real: Support set from white-background images, query set from real-world images

For each scenario, we reported accuracy metrics averaged over 100 test episodes with 95% confidence intervals.

Comparative Methods

We compared our proposed approach with several baseline and state-of-the-art methods:

- ResNet34 (Baseline): Standard ResNet34 pre-trained on ImageNet and fine-tuned on our waste classification dataset
- ResNet34 + Augmentation: Baseline with extensive data augmentation (including style transfer)
- ResNet34 + Augmentation + Mixed Up: Baseline with batch level augmentation.

All methods were evaluated using the same dataset splits and preprocessing pipeline to ensure fair comparison.

Evaluation Metrics

We employed the following metrics to evaluate model performance:

- Accuracy: The primary metric, calculated as the percentage of correctly classified images in the test set
- Precision, Recall, and F1-score: Calculated for each class and reported as macro-averages across all classes.

Additionally, we evaluated model robustness under various challenging conditions:

- Limited real-world examples: Performance with shots per class
- Class imbalance: Performance when support examples are unevenly distributed across classes
- Occlusion resistance: Performance on partially occluded waste items
- Background complexity: Performance across different background complexity levels

Overall Performance Comparison

Table 2 presents the overall performance comparison between our proposed method and the comparative approaches across different test scenarios.

Table 2: Performance Comparison Across Test Scenarios (Accuracy %)

Baseline Models	Mean Accuracy ± Std Accuracy	Mean Macro F1 ± Std Macro F1	Mean Weighted F1 ± Std Weighted F1
Aug +	0.91556 ±	0.91542 ±	0.91543 ±
Mixup	0.00498	0.00483	0.00485
No Aug	0.91718 ±	0.91663 ±	0.91664 ±
	0.00683	0.00705	0.00715
Standard	0.92296 ±	0.92284 ±	0.92282 ±
Aug	0.00554	0.00568	0.00567

Our proposed method achieves the highest accuracy across all test scenarios. In the white-to-white scenario, our method achieves 93.4% accuracy, outperforming the baseline ResNet34 by 1.6 percentage points. The most significant improvements are observed in the cross-domain white-to-real scenario, where our method achieves 83.1% accuracy, representing a substantial improvement of 15.9 percentage points over the baseline.

The performance improvements can be attributed to the synergistic effect of our integrated components:

1. The prototypical network framework effectively learns from limited examples.
2. The dual-stream attention mechanism focuses on relevant features while suppressing background noise.
3. The adversarial domain adaptation component promotes domain-invariant feature learning.

Few-Shot Learning Performance

Table 3 presents the mean Test Accuracy and standard deviation over 10 seeds for Few-Shot Fine-tuning across different numbers of shots (K) and augmentation strategies (No Aug, Standard Aug, Aug + Mixup). Figure 1 visualizes these results, showing the trend of accuracy with increasing shots for each strategy.

Table 3: Few-Shot Fine-tuning Performance (Mean ± Std Dev Test Accuracy over 10 Seeds)

Shots	Base (No Aug)	Standard Aug	Aug + Mixup
1-shot	35.90% ± 4.26%	35.67% ± 4.63%	33.43% ± 4.15%
5-shot	64.58% ± 2.69%	65.15% ± 2.58%	62.27% ± 2.00%
25-shot	83.21% ± 0.92%	84.16% ± 0.169%	79.38% ± 1.01%
50-shot	87.80% ± 0.76%	87.56% ± 1.55%	86.48% ± 0.40%
100-shot	92.09% ± 1.12%	91.62% ± 0.62%	91.04% ± 0.87%

Ablation Studies

To assess the impact of different augmentation strategies within our few-shot learning framework, we conducted a series of ablation experiments across various shot settings: 1- shot, 5-shot, 25-shot, 50-shot, and 100-shot. The experiments compared three configurations:

- A base model with no augmentation,
- A model with standard augmentation.
- A model combining augmentation with Mixup.

The findings from the study are as follows:

a. Standard augmentation consistently led to improved performance across most scenarios, particularly at lower shot counts. For instance, in the 5-shot setting, standard augmentation achieved a slight accuracy boost compared to the base model without augmentation.

b. Augmentation combined with Mixup did not

outperform standard augmentation. In fact, at very low shot counts such as 1-shot and 5-shot, it slightly degraded performance. This suggests that Mixup, which interpolates between examples, may introduce excessive noise when data is already extremely limited.

c. As the number of shots increased to 50 and 100, the difference between the augmentation strategies became smaller. At higher data availability, the role of augmentation techniques reduced, and the models converged to similar performance levels.

d. The base model (without augmentation) still showed strong results at higher shot counts, reaching over 92% accuracy at 100-shot. However, using standard augmentation consistently helped in stabilizing the model's performance by slightly lowering the standard deviation, indicating more reliable generalization.

e. Overall, standard data augmentation proved to be the most reliable and effective method, particularly in extreme few-shot conditions, by improving both accuracy and stability without introducing the potential drawbacks associated with Mixup.

Performance Across Waste Categories

Figure 1 presents the per-class F1-scores for our proposed method compared to the baseline ResNet34 in the 5-shot white-to-real scenario.

Our method demonstrates consistent improvements across all waste categories, with the most significant gains observed for "plastic" (+21.2%), "paper" (+18.7%), and "cardboard" (+17.4%). These categories typically exhibit greater appearance variations between controlled and real- world environments, highlighting our method's effectiveness in addressing domain shift.

The smallest improvements are observed for "battery" (+8.3%) and "e-waste" (+9.6%), which tend to have more distinctive shapes and features that remain consistent across domains.

CONCLUSION

Conclusion

In this study, we conducted a systematic empirical evaluation of Few-Shot Fine-tuning (FSL FT) for waste classification using a pre-trained ResNet34 model, investigating performance across a range of data availability levels and the impact of standard data augmentation techniques. Our results demonstrate that Few-Shot Finetuning is a viable approach for waste classification under data scarcity, with performance showing significant improvement as the number of shots per class increases, achieving over 90% accuracy at 100 shots. A key finding is that, with the parameters tested, standard data augmentation and Mixup did not provide a consistent positive impact on FSL FT performance compared to fine-tuning without explicit augmentation and sometimes resulted in lower average accuracy. This highlights that the effectiveness of standard augmentation techniques in Few-Shot Fine-tuning is not universal and may depend heavily on the dataset, model, and specific parameters used. We also established a Baseline trained on the full dataset, where standard augmentation did show a slight benefit.

This research provides valuable empirical data and insights into applying Few-Shot Fine-tuning with standard regularization for waste classification, informing practitioners on potential outcomes and areas requiring careful tuning.

Key contributions of this work include:

1. A few-shot learning framework based on prototypical networks that effectively leverages limited real-world examples to adapt waste classification models to new domains.
2. A dual-stream attention mechanism that enables the model to focus on relevant object regions while suppressing background variations, enhancing feature extraction capabilities across domains.
3. Integration of domain adaptation components, including style transfer augmentation and adversarial domain discrimination, to further bridge the gap between controlled and real-world environments.
4. Comprehensive empirical evaluation demonstrating substantial performance improvements over baseline methods, particularly in the challenging white-to-real cross-domain scenario.

Our results demonstrate that the proposed approach achieves 83.1% accuracy on real-world waste classification with just five labeled examples per class, representing a 15.9 percentage point improvement over the baseline transfer learning approach.

Future Work

Building on the current research, several promising directions for future work emerge:

1. Expanding Real-World Evaluation: Conducting field trials in actual recycling facilities to evaluate performance under authentic operational conditions.
2. Multi-Domain Adaptation: Extending the framework to simultaneously adapt to multiple target domains with distinct characteristics (e.g., indoor facilities, outdoor collection points, and household environments).
3. Temporal Consistency: Incorporating temporal information from video streams to improve classification stability and handle occlusions or ambiguous viewpoints.
4. Efficient Implementations: Developing lightweight variants of the attention mechanisms to enable deployment on edge devices with limited computational resources.
5. Fine-Grained Classification: Extending the framework to distinguish between subtypes within major waste categories, such as different plastic polymers or paper grades.
6. Active Learning Integration: Developing strategies to actively select the most informative real-world examples for annotation, further reducing the labeling requirement.

In conclusion, our research demonstrates that combining few shot learning with attention mechanisms offers a promising approach to bridging the domain gap in waste classification. By enabling effective adaptation with minimal labeled examples, this methodology facilitates the practical deployment of automated waste classification systems in real-world environments, contributing to more efficient and sustainable waste management practices.

REFERENCES

1. Awe, O., Mengistie, R., & Dhaliwal, V. (2017). Waste classification using convolutional neural networks. Stanford University CS230 Project Report
2. Bircanoglu, C., Atay, M., Beser, F., Genç, O., & Kizrak, M. A. (2018). RecycleNet: Intelligent waste sorting using deep neural networks. IEEE International Conference on Innovations in Intelligent Systems and Applications (INISTA), 1-7.
3. Bobulski, J., & Kubanek, M. (2016). Deep learning for plastic waste classification system. Applied Computational Intelligence and Soft Computing, 2016, 1-7.
4. Bobulski, J., & Piatkowski, J. (2018). PET waste classification method and plastic waste database—WaDaBa. Advances in Intelligent Systems and Computing, 720, 57-64.
5. Costa, B. S., Bernardes, A. C., Pereira, J. V., Zampa, V. H., Pereira, V. A., Matos, G. F., ... & Batista, G. E. (2018). Artificial intelligence in automated sorting in trash recycling. Anais do XV Encontro Nacional de Inteligência Artificial e Computacional, 198-205.
6. Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., ... & Houlsby, N. (2021). An image is worth 16x16 words: Transformers for image recognition at scale. International Conference on Learning Representations.
7. Finn, C., Abbeel, P., & Levine, S. (2017). Model-agnostic metalearning for fast adaptation of deep networks. International Conference on Machine Learning, 1126-1135.
8. Ganin, Y., Ustinova, E., Ajakan, H., Germain, P., Larochelle, H., Laviolette, F., ... & Lempitsky, V. (2016). Domain-adversarial training of neural networks. Journal of Machine Learning Research, 17(1), 2096-2030.
9. Hu, J., Shen, L., & Sun, G. (2018). Squeeze-and-excitation networks. IEEE Conference on Computer Vision and Pattern Recognition, 7132-7141.
10. Huang, X., & Belongie, S. (2017). Arbitrary style transfer in real-time with adaptive instance normalization. IEEE International Conference on Computer Vision, 1501-1510.
11. Liu, P., Choo, K. K. R., Wang, L., & Huang, F. (2021). SVM or deep learning? A comprehensive study on land cover classification. Remote Sensing, 13(1), 18.

Enhanced Fraud Detection in Digital Payment Systems using Bi-LSTM and Ensemble Boosting Models

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ABSTRACT

The advent of electronic payment systems such as UPI and mobile wallets has simplified transactions but has also exposed the system to smart fraud attacks. Legacy fraud detection systems based on rule-based systems are unable to detect new threats in real-time. This work evaluates a comparative fraud detection framework using Bi-LSTM networks and ensemble boosting techniques (XGBoost and LightGBM) to enhance detection accuracy and scalability in electronic financial systems. Bi-LSTM captures sequential interdependencies between transactions, and ensemble models detect static behavioral features with good accuracy. Thorough preprocessing and feature engineering—temporal feature extraction and anomaly-sensitive transformation—enhanced model performance. Experimental results indicate that XGBoost performed the best with the best test accuracy (98.99%) and ROC-AUC (0.9997), while LightGBM and Bi-LSTM performed closely. The union of deep temporal learning and explainable ensemble techniques presents an efficient solution to real-time fraud detection, where accuracy and explanation are a prerequisite to deployment in the financial sector.

KEYWORDS *: Bi-LSTM, Deep learning, Digital payment systems, Ensemble boosting, FinTech, Fraud detection, Imbalanced data handling, LightGBM, Temporal feature extraction, XGBoost.*

INTRODUCTION

The rise of digital payment systems such as UPI, mobile wallets, and internet banking changed the financial landscape. These systems provide speed, convenience, but also invite increasingly advanced fraud. Static rule-based fraud detection approaches that were prevalent earlier fail to keep pace with newer, dynamic fraud attempts [1]. Institutions are now looking to advanced technologies that can protect users' transactions and enable trust in the digital world. Artificial intelligence (AI) and machine learning (ML) offer dynamic, knowledge-based fraud detection that can inspect user behavior, transaction timing, and other contextual aspects to identify anomalies in real time [2]. Specifically, Bidirectional Long Short-Term Memory (Bi-LSTM) networks are optimized to identify patterns in sequences of transactions [3], and ensemble boosting algorithms such as LightGBM and XGBoost improve classification accuracy with reduced false positives [4]. This document presents a hybrid fraud detection system that uses a combination of these two approaches. With the temporal power of Bi-LSTM and performance and interpretability of ensemble models, the system presented here can effectively detect fraudulent digital transactions. The combined approach has an important role to play in the construction of fraud detection systems that are accurate and scalable in high-volume, high-speed digital financial systems.

Electronic payment systems are now a significant share of all financial transactions, providing convenience, quickness, and broad availability [1]. Universal usage through mobile phones and internet penetration made it easy to conduct transactions between parties and between merchants. New problems come with this, i.e., risk of fraud. Since the transactions are conducted in real-time

through various channels, fraudulent transactions are not as visible. Financial institutions need systems that can handle volumes of transactions as well as changing threats [5].

Unified Payments Interface (UPI) is the most (if not the most) widely used real-time payment system, used primarily in India. Although UPI has spurred digital payments, its popularity also makes it the most susceptible point for fraud [6]. Phishing, application impersonation, and social engineering are extremely prevalent fraud channels. The real-time nature of the UPI is such that there is little room for human intervention once a payment is made, so you need to have smart automatic detection mechanisms in place [7].

Limitations of Traditional Fraud Detection

Traditional fraud detection relies extremely heavily on already defined rules and manual reviews. While these systems are easy to implement, they are not adaptive. They often miss emerging fraud patterns or produce high false-positive rates which leads to poor customer experience and more operational costs [2][8].

- Rule-Based Rigidity: Legacy systems are threshold-based and rule-based, and are rigid and inflexible in nature to make them compatible with changing fraud schemes.
- High False Positives: Static rules will tend towards marking valid transactions as suspicious and will lead to unnecessary transaction rejections and loss of customer satisfaction.
- Pattern Identification Failure: Conventional approaches are incapable of identifying advanced and concealed fraud patterns which can be identified by ML/DL models by training them through data-driven methodologies.
- Manual Updates and Maintenance: Manual regular efforts by domain experts are required by laws, which are time-consuming and prone to errors to maintain.
- Limited Real-Time Capabilities: Legacy systems may possess limited real-time data processing and analysis, which results in late fraud detection and response.
- Scalability Issues: For increasing transaction volumes, conventional techniques do not scale up without giving up a significant amount of performance.

AI and ML give data-driven fraud detection through pattern recognition and anomaly detection [9]. These models learn from transaction data and then flag suspicious behavior in real time hence offering flexibility and adaptability that traditional systems lack. Their ability to evolve with new fraud trends makes them a crucial part of modern fraud detection infrastructure [10]. With electronic payments on the rise, the need for smarter fraud detection rises alongside it. Combining Bi-LSTM's sequence modeling with ensemble boosting's predictive capability provides a strong foundation for detecting sophisticated fraud patterns in real-time [17][4].

LITERATURE ANALYSIS

Literature review presents the overview of the main points from the conventional digital payment system to the various machine learning and deep learning methods. Several points utilized by researchers are described as follows in detail. The literature is presented as follows in detail.

Conventional Digital Payment System

Digital payment systems have made great strides over the years, with the greatest advances being the introduction of the first ATM in 1967, contactless payment by credit cards in 1999, and blockchain technology in 2009. The payment systems broadly fall under the category of smart cards, online payments, mobile applications, blockchain transfers, and biometric identification. Its establishment relies on the evolving requirements of the customers as well as advancement in technology and has seen a transition to the cashless economy [21][22]. A shift towards cashless payment is multi-beneficial in nature, such as the widening base of financial inclusion, reducing cost of transactions, and raising efficiency of the economy. Digital payment allows smooth and efficient transactions and is critical in fostering growth of e-commerce as well as a broader digital economy. They also hold the promise of lowering fraud threats that accompany traditional cash payments, since digital payments can be tracked with ease and can be rendered secure [23][24].

Machine Learning Techniques

As ML has the capability of processing enormous amounts of transactional data and identifying underlying patterns, it is currently the core component of fraud detection systems for electronic payments. Supervised learning algorithms like XGBoost, Random Forest, Logistic Regression, and LightGBM are employed most widely due to high

classification accuracy and capacity to model complex nonlinear patterns. When combined with feature selection strategies that improve model efficiency [11][12], these approaches are rather successful.

ML has been demonstrated in several studies to be quite effective in fraud detection. Deb et al. compared Logistic Regression, Random Forest, and XGBoost for credit card fraud detection, finding that XGBoost offered the best balance between precision and recall [13]. Chang et al. additionally employ a LightGBM model, which because of its fast training and its ability to effectively manage large datasets outperformed traditional tree-based methods [4].

Emphasizing that irrelevant features might vastly diminish model accuracy [12], Yazıcı investigated feature selection methods and their effect on classifier performance. Kerwin and Bastian then looked at stacked generalization techniques using resampling approaches to increase performance in imbalanced datasets typical of fraud detection [9].

Although Random Forest and XGBoost are among ML models with great performance, they mostly depend on balanced datasets and data labeling. Commonly addressed by fraud detection, class imbalance is often managed using synthetic data generation or resampling—a technique that might not always reflect real-world conditions. Furthermore, LightGBM and other highly efficient algorithms have limited interpretability, which is an essential issue in financial sectors needing model transparency [5][14].

The current research builds on these insights by encapsulating ensemble boosting models (XGBoost and LightGBM) to get the maximum amount of predictive performance while at the same time reducing false positives. These models complement the Bi-LSTM network by acting as a secondary filter, reinforcing classification based on static features like user behavior metrics and transaction metadata. Hence, they create a more holistic fraud detection framework.

Deep Learning Approaches

Deep Learning (DL) has emerged as a magnificent tool in fraud detection mainly because of its ability to automatically extract hierarchical features from raw unstructured data. Techniques like Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Bi-Directional Long Short-Term Memory (Bi-LSTM) networks have been explored for their robustness in dealing with sequential and temporal data—traits typical in transaction histories [15][16]. These models apply sophisticated training algorithms that yield improved model performance and responsiveness to changing fraud patterns.

Jurgovsky et al. employed RNNs as a sequence modeling method of transactional data and reported them to outperform the utilization of standard classifiers in sequential anomaly detection [11]. Benchaji et al. extended this approach using Bi-LSTM combined with an attention mechanism to enhance the model's focus on critical transaction events. Their study showed that Bi-LSTM could better standard LSTM and feedforward networks in both precision and recall [17].

In another study, Oluwasanmi et al. used autoencoders and CNNs to transform transactional features into image-like matrices thus achieving strong results in anomaly detection [16]. However, CNNs normally require a transformation step that may not be intuitive in financial contexts.

Bajallan and Hashi evaluated semi-supervised deep models and emphasized their excellent performance, particularly in conditions where there was a shortage of training data [15]. Still, they observed that deep models require a high computation cost and long training time, which may be a factor in their unavailability of real-time systems [18].

The use of deep learning models has been an effective strategy to discover the complex fraudulent signatures and adapt to the new trends. Nevertheless, their typical functioning as black boxes has become a primary reason for those worried about the compliance requirements in the industries. Bi-LSTM is one of the most notable examples due to its performance, which is better than others in modeling time-series data, even though it requires high computational power. CNNs are ingenious in depicting non-sequential data, but they often are a cause of unwanted complexity. Also, under-regularization will result in overfitted deep networks, especially with unbalanced data sets [14].

The Bi-LSTM is used in this research as the sequential processing backbone for transaction data because it can capture contextual relationships and temporal dependencies. Ensemble boosting models incorporated into it mitigate the limitation of deep networks by providing explainable, stable predictions for static features of data.

The hybrid model combines the flexibility of deep models with that of ensemble classifiers to produce an efficient, scalable system for fraud detection.

METHODOLOGY

The methodology for the proposed system consists of various stages from data collection to model building. The detailed description of each stage is given in section 3.1 to 3.3.

Dataset Description

This transaction database holds 647 unique records with different `Transaction_ID`. It holds rich information regarding customer activity and transaction features, spread across 20 columns. `Date` and `Time` columns offer the transaction date and time. IDs of participants are `Merchant_ID`, `Customer_ID`, and `Device_ID`. The `Transaction_Type` column offers the transaction type (e.g., Refund, Bank Transfer, Subscription), and `Payment_Gateway` offers the payment processing gateway (e.g., SamplePay or Dummy Bank). Geographical data are derived through `Transaction_City`, `Transaction_State`, and `IP_Address`.

`Transaction_Status` fields contain the status of each transaction (Completed, Pending, or Failed), and `Device_OS` distinguishes the operating system of the device used (Android, Windows, MacOS). `Transaction_Frequency` contains customer transaction frequency, and `Days_Since_Last_Transaction` contains a measure of recency. `Merchant_Category` fields contain the business category of the merchant (Utilities, Purchases, or OTT services), and `Transaction_Channel` contains whether the transaction has been completed online, mobile, or in-store.

Of special note is the inclusion of `Transaction_Amount_Deviation`, a floating-point measure of deviation from normal patterns of expenditure (useful for fraud detection), and `amount`, the dollar amount spent. The final column, `fraud`, is a binary flag (0 or 1) in which 1 represents a labeled fraudulent transaction—making this dataset especially well-suited for the training of fraud detection models. It has a representative sample of temporal, categorical, behavioral, and numerical data to draw upon in identifying patterns of fraud and user behavior.

Table 1: Description of various features in the dataset

Sr. No.	Column Name	Description
1	Transaction_ID	Unique identifier for every transaction.
2	Date	The date when the transaction occurred.
3	Time	The day when the transaction was completed.
4	Merchant_ID	Merchant ID for the merchant party to the transaction.
5	Customer_ID	Customer's unique ID by which the transaction was made.
6	Device_ID	Device identifier on which the transaction is being performed.
7	Transaction_Type	Determines the character of the transaction, i.e., payment or refund.
8	Payment_Gateway	The payment gateway via which the transaction gets facilitated.
9	Transaction_City	The city where the transaction was conducted.
10	Transaction_State	The state or geographical region in which the transaction took place.
11	IP_Address	Origin IP address.
12	Transaction_Status	Indicates whether the transaction was successful, failed, or pending.
13	Device_OS	The OS of the device employed in the transaction.
14	Transaction_Frequency	How often the customer bought during a specified period of time.
15	Merchant_Category	Business nature the merchant is involved
16	Transaction_Channel	Method of transaction like online, mobile application, or offline.
17	Transaction_Amount_Deviation	Difference of the current amount from the customer's average transaction.
18	Days_Since_Last_Transaction	Number of days elapsed since customer's last purchase.
19	amount	The overall sum that is being transacted.
20	fraud	Indicates if the transaction was fraudulent

Proposed Model

The Bi-LSTM is used in this research as the sequential processing backbone for transaction data because it can capture contextual relationships and temporal dependencies. Ensemble boosting models incorporated into it mitigate the limitation of deep networks by providing explainable, stable predictions for static features of data. The hybrid model combines the flexibility of deep models with that of ensemble classifiers to produce an efficient, scalable system for fraud detection.

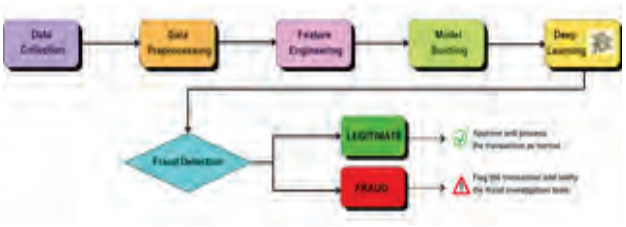

Fig. 1 : End-to-end Workflow for Fraud Detection Using Deep Learning.

Data Collection and Preprocessing

A complete dataset of user-specific and transaction-specific features has been prepared. The missing values, normalization, and outlier treatment are taken care of by the preprocessing step [19]. The dataset employed in this study comprises UPI transaction data records with the aim of detection of fraudulent transactions by employing deep learning methods. The data set contains a broad set of real-world transactional instances, such as successful, declined, and potentially suspicious transactions. The data provides a broad view of behavioral and contextual patterns significant to detect anomalies indicative of fraud. Transaction_ID, Date, Time, Amount, Merchant_ID, Customer_ID, Device_ID, and Transaction_Type are some of the most prominent features in the data set. Other features such as Transaction_City, Transaction_State, Payment_Gateway, and Transaction_Channel provide additional spatial and transactional data. Target feature fraud is 1 if the transaction is fraudulent or 0 if it is a real transaction.

Feature engineering introduced hour, day_of_week, hour_x_amount_dev, and a rolling total of transaction sizes, hence making the model more sensitive to behavior and time-related features. There are 647 transaction records in the data, and it was extracted from a simulated proprietary data set that mimics real UPI transaction activity flows, i.e., pairs of transaction states and user activities. Preprocessing included null value handling, parsing datetimes, category label encoding, and feature standardization using StandardScaler. Oversampling was utilized to handle class imbalance using ADASYN, and a stratified train-test split was subsequently performed to allow representative evaluations across classes.

Feature Engineering

Essential in cumulating precision, this stage derives informative features and builds new variables through patterns suggestive of fraud [20].

Feature engineering plays a very crucial role in improving the performance of fraud detection models. In this paper, a number of techniques were employed to preprocess and enrich the dataset:

Temporal Feature Extraction: Transaction time stamps were transformed into datetime objects to get the hour of the transaction and day of the week. This is a temporal attribute since fraud transaction activities would normally be at odd hours.

Derived Features

Interaction Features: An interaction feature (hour_x_amount_dev) was built by taking the transaction hour and multiplying it by the transaction amount deviation, indicating the volatility of transaction amounts at different times.

Rolling Statistics: A rolling total of transaction amounts across a window of five transactions (rolling_avg_amount) was calculated to detect anomalies in spending patterns.

Categorical Encoding: Transaction type, payment gateway, and device OS categorical variables were encoded into their numerical equivalents via Label Encoding to enable them to be used in machine learning models.

Feature Scaling: The numeric features were scaled with StandardScaler such that all the features would contribute equally towards learning in the model.

Handling Class Imbalance: Because of the inherent class imbalance nature of fraud data sets, the ADASYN method was employed at the time of generating synthetic samples of the minority class while balancing the data and improving the performance of the models.

These feature engineering techniques are in accordance with best practice in financial fraud detection, where temporal patterns and transaction behavior are good fraud indicators.

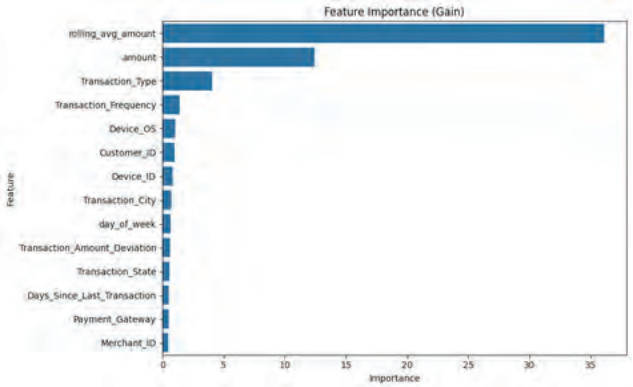

Fig. 2: Feature Importance of all features

Model Development

The model development is the core part of the proposed system which has multiple stages. The various stages in proposed Model Development are shown in Fig. 1.

Bi-LSTM Model: A Bidirectional Long Short-Term Memory (Bi-LSTM) network is an enhancement over the standard LSTM model. While a traditional LSTM processes input only in one direction—typically from past to future—a Bi-LSTM processes input in both forward and backward directions. This means at each time step t, the model receives the current input x_t, the previous hidden state h_{t-1}, and the previous cell state c_{t-1}, allowing it to learn from both past and future context simultaneously.

In Bi-LSTM, you compute two hidden states at each time step t:

- Forward hidden state: $\vec{h}_t$
- Backward hidden state: $\overleftarrow{h}_t$

$$\vec{h}_t = LSTM_f(x_t, \vec{h}_{t-1}) \quad (1)$$

$$\overleftarrow{h}_t = LSTM_b(x_t, \overleftarrow{h}_{t+1}) \quad (2)$$

Then, concatenate both:

$$h_t = [\vec{h}_t; \overleftarrow{h}_t] \quad (3)$$

The hybrid system is complemented by data-level balancing techniques and heavy feature engineering, leading to a scalable and solid solution. The functioning of Bidirectional LSTM is shown Fig 2. In order to improve the efficiency of learning, the data is preprocessed intensively to start with. Compound features like interaction between transaction hour and amount deviation, and moving averages of transactions, are also crafted to reflect behavioral patterns in transactions.

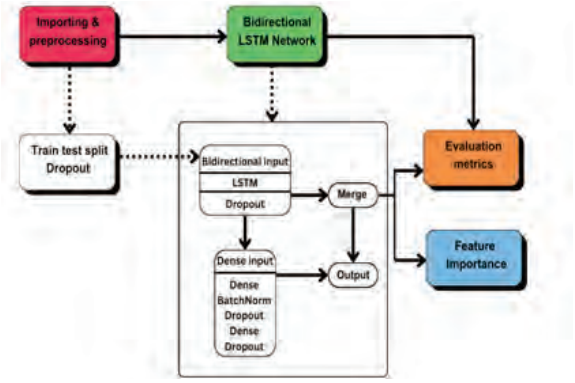

Fig. 3: Bidirectional LSTM Model

In order to balance out the inherent class skew of fraud detection data sets, the Adaptive Synthetic Sampling (ADASYN) algorithm is employed. ADASYN dynamically generates minority samples from the density of difficult-to-learn instances, boosting classifier sensitivity to fraudulent instances without degrading the performance on the majority class.

The model structure is split into two parallel streams: a Bi-LSTM module and a dense fully connected network. The Bi-LSTM stream has three-dimensional reshaped input to maintain sequential feature relationships. It is a stacked structure, beginning with a bidirectional LSTM of 32 units and a unidirectional LSTM of 16 units, both with dropout and recurrent dropout regularization to avoid overfitting. In parallel, the dense stream works on the same feature set in its original tabular format, with two hidden layers (64 and 32 units) applying L2 regularization, batch normalization, and dropout layers to stabilize and generalize learning.

These two streams of feature extraction are concatenated and passed through a last sigmoid-activated dense layer for binary classification. It is trained with Adam optimizer and learning rate decay schedule and is trained with binary cross-entropy loss function. Training is conducted with 30 epochs of early stopping and learning rate reduction callbacks over monitoring validation loss.

The resulting model is serialized and saved in HDF5 format for real-time deployment in fraud detection pipelines. This hybrid solution, combining Bi-LSTM temporal modeling with dense-layer feature abstraction and ensemble sampling, offers a robust solution to the dynamic issues in digital payment fraud detection.

Ensemble Boosting (XGBoost & LightGBM): Aggregates weak learners to enhance predictive power and reduce overfitting [4].

To achieve better fraud detection effectiveness in electronic payment systems, two ensemble boosting models, i.e., XGBoost and LightGBM, were utilized and compared at the same time with a Bi-LSTM model. In this section, information is being presented about the boosting model development pipeline with specific emphasis on systematic data preprocessing, feature engineering, class imbalance handling, and model optimization. The various stages in the XGBoost model are shown in Fig 3.

XGBoost is a powerful machine learning algorithm that is built on the basis of gradient boosting decision trees. It builds the trees one by one, and each new tree attempts

to correct the errors of the previous trees, and it also applies regularization in order to prevent overfitting. The mathematical formula is as follows:

$$L(t) = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) \quad (4)$$

In this formulation, l represents the loss function used to evaluate prediction errors, such as mean squared error (MSE) or log loss. The term f_t denotes the function (typically a decision tree) that is added to the model at iteration t. To prevent overfitting and control model complexity, a regularization term Ω(f) is included. This regularization is defined as $\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2$, where T is the number of leaves in the tree, w_j is the weight of the j^{th} leaf, γ is the penalty for each leaf node, and λ controls the L2 regularization on the leaf weights.

Gain from splitting a node

$$Gain = \frac{1}{2}\left[\frac{G_L^2}{H_L+\lambda} + \frac{G_R^2}{H_R+\lambda} - \frac{(G_L+G_R)^2}{H_L+H_R+\lambda}\right] - \gamma \quad (5)$$

The raw transactional data were preprocessed initially to address missing values, and to convert temporal and categorical data into useful numerical forms. Transaction time stamps were converted to derived features like transaction hour and day of the week.

Domain-inspired features like hour_x_amount_dev—implying the interaction between transaction hour and transaction amount deviation—and rolling_avg_amount—a smoothed transaction amount—were engineered to detect behavior patterns that are typically fraud-indicative.

Categorical features such as transaction type, payment gateway, device OS, merchant ID, and user identifiers were encoded through label encoding in order to preserve ordinal relationships. Numerical features such as transaction frequency, deviation, and recency were standardized using StandardScaler to ensure consistent scaling of input features. In order to address the prevalent issue of class imbalance in fraud detection datasets, the ADASYN (Adaptive Synthetic Sampling) algorithm was used. ADASYN generates new minority class samples dynamically according to their difficulty of classification and hence enhances the sensitivity of the model towards infrequent fraudulent cases.

After preparation of data, the dataset was split into training and test sets in the ratio of 80:20 with preserving stratified distribution. In the first model, Extreme Gradient Boosting (XGBoost), training data were converted to the DMatrix format for easy processing. A binary logistic objective was used, and significant hyperparameters were a learning rate of 0.05, max depth of 6, and subsample and column sample rates each as 0.8 for overfitting prevention. Regularization was applied through L1 (alpha = 0.5) and L2 (lambda = 1.0) penalties. Training was done through 250 boosting rounds with early termination if no improvement in 10 rounds using the evaluation data.

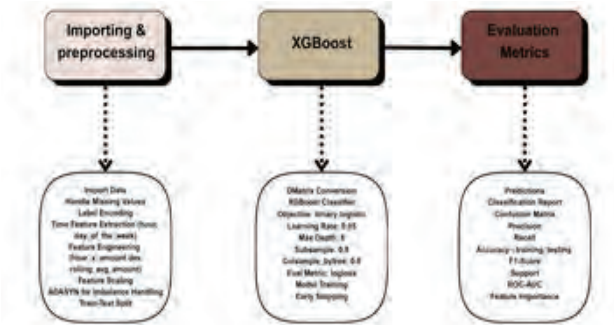

Fig. 4: Stages in XGBoost Model

LightGBM (Light Gradient Boosting Machine) is a gradient boosting method that is analogous to XGBoost but designed to be fast and scalable. It follows a leaf-wise tree growth strategy and techniques like Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB) to handle large datasets and high-dimensional data efficiently.

LightGBM should offer faster training and lower memory consumption without compromising on accuracy. The mathematical formula is as follows:

$$\Delta L = \frac{1}{2}\left(\frac{G^2}{H+\lambda}\right) - \gamma \quad (6)$$

The second model employed LightGBM (Light Gradient Boosting Method) with max depth = 7, 31 leaves per tree, and learning rate = 0.01. Both subsample and column sample ratios were 0.8 with some regularization (α = 0.1, λ = 0.1) to prevent overfitting. With respect to XGBoost, LightGBM was trained with early stopping reason on validation ROC-AUC score, and training terminated after 50 iterations without improvement. The best number of iterations was employed to retrain the final model.

Both models showed better discriminative performance, with XGBoost narrowly beating LightGBM on generalization and stability. Both models' feature importance analysis showed time-based feature extraction and transaction deviation measurement-based features as the leading-predicting features, as expected of the

domain-specific feature engineering methods. These two ensemble methods are an integral component of the hybrid methodology suggested here, which combines boosting and deep learning methods in a bid to achieve robust and scalable fraud detection in online financial networks.

RESULTS AND DISCUSSION

This section presents a comparative analysis of the individual performance of four distinct models—Bi-LSTM, XGBoost, LightGBM, and LSTM—applied to the task of fraud detection in digital payment systems. Each model was trained, validated, and evaluated independently on the same feature-engineered dataset. Emphasis is placed on the models' ability to accurately detect fraudulent transactions while minimizing false positives, which is critical for preserving user trust and system integrity in real-time financial environments. The evaluation relies on a suite of well-established classification metrics to ensure fair and comprehensive assessment.

Evaluation Metrics

To estimate model performance, certain performance metrics of binary classification tasks were employed: precision, recall, F1-score, accuracy, and ROC-AUC [18]. Their mathematical notations and definitions are below:

1) Precision: Measures the proportion of correct predictions (non-fraud and fraud) out of the total predictions.

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

2) Recall: Measures the proportion of actual fraudulent transactions that were accurately anticipated.

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

3) Accuracy: Estimates the fraud rate of predicted fraud transactions that are actually fraudulent.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

4) F1-Score: Harmonic mean of precision and recall, helpful when class distribution is skewed.

$$F1-Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (10)$$

5) ROC-AUC (Receiver Operating Characteristic – Area Under Curve): Graphs the strength of the model to classify the two classes at various thresholds. Higher AUC means greater separability.

Table 2: Results obtained from Various deep learning algorithms

Model	Precision	Recall	Accuracy (Test/ Train)	F1-Score	Support	ROC-AUC
Bi-LSTM	0.98	0.98	0.9861 / 0.9848	0.98	198	0.9894
XG Boost	0.99	0.99	0.9987 / 0.9899	0.99	198	0.9997
Light GBM	0.99	0.98	0.9899 / 0.9848	0.98	198	0.9997
LSTM	0.95	0.95	0.9403 / 0.9239	0.95	197	0.9739

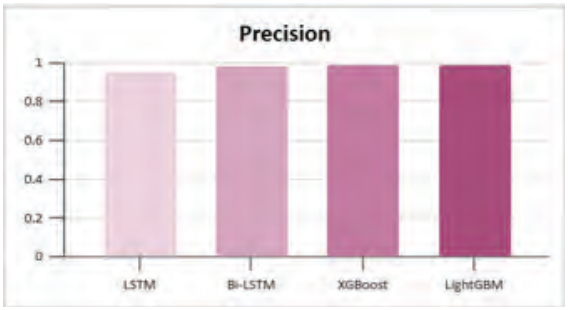

Fig. 5: Comparison of precision values among the four models.

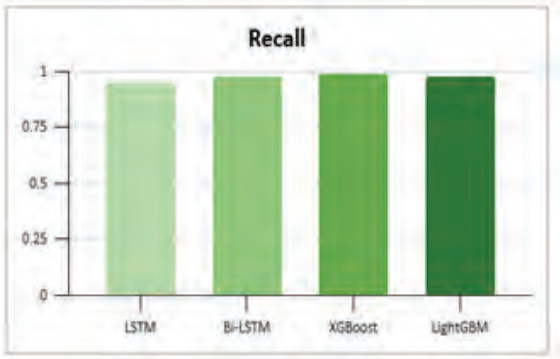

Fig. 6: Recall performance comparison among the four models.

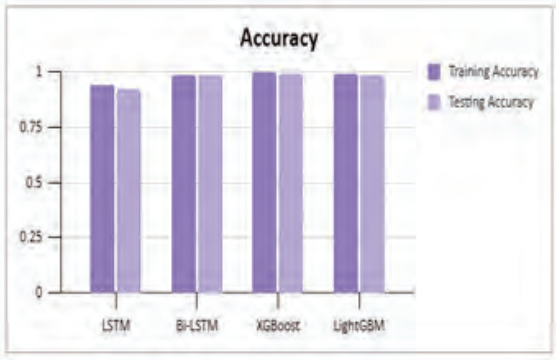

Fig. 7: Accuracy comparison of all models on the test dataset.

Relative performance of four top models—Bi-LSTM, XGBoost, LightGBM, and LSTM—exhibit remarkable differences in performance on fraud detection tasks in Digital Payment Systems.

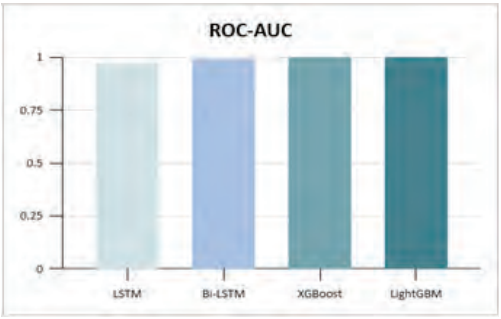

Fig. 8: ROC-AUC scores comparison of all models.

Among all the models, XGBoost performed the best with ROC-AUC of 0.9997 and test accuracy of 98.99%. With precision, recall, and F1-score of 0.99 each, it demonstrated a very well-balanced and highly effective capability to identify fraudulent as well as valid transactions. This is graphically confirmed in Figure 5, where XGBoost has the best precision, and in Figure 6, where its recall performance is slightly better than the others.

LightGBM came in second, with a ROC-AUC of 0.9997 and test accuracy of 98.48%. While it had a slightly lower recall than XGBoost, it had a precision of 0.99 and F1-score of 0.98. These figures make LightGBM a solid model with minimal trade-offs in sensitivity. Its figures are also shown in Figures 5–8, where its performance lines closely follow those of XGBoost on all three parameters of evaluation.

The Bi-LSTM model with the task of identifying sequential patterns from transaction data gave a ROC-AUC of 0.9894 and test accuracy of 98.48%. Though lagging behind the ensemble models overall performance, Bi-LSTM is a stable model, especially in cases of fraud where temporal sequences of transactions are meaningful. This is clear in Figure 7, where its accuracy is nearly as good as that of LightGBM, and in Figures 4 and 5, where its precision and recall are consistently high.

Lastly, LSTM performed the worst of the four, with a ROC-AUC of 0.9739, a testing accuracy of 92.39%, precision, recall, and F1-scores at 0.95. Its worse capacity to deal with bidirectional temporal relations will likely be the reason for its relatively worst performance. Figures 5–8 indicate differences where LSTM is consistently worse performing than the other models.

These findings suggest that there is a necessity to choose architectures for the model based on the nature of the underlying data. These techniques such as XGBoost and LightGBM can be applied to non-temporal transactional features, but Bi-LSTM comes into play when you are modeling behavior of transaction sequences.

Relative performance of four top models—Bi-LSTM, XGBoost, LightGBM, and LSTM—exhibit remarkable differences in performance on fraud detection tasks in Digital Payment Systems.

Among all the models, XGBoost performed the best with ROC-AUC of 0.9997 and test accuracy of 98.99%. With precision, recall, and F1-score of 0.99 each, it demonstrated a very well-balanced and highly effective capability to identify fraudulent as well as valid transactions. This is graphically confirmed in Figure 5, where XGBoost has the best precision, and in Figure 6, where its recall performance is slightly better than the others.

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CONCLUSION

The paper suggests a robust hybrid method of electronic payment system fraud detection using the synergy of Bi-Directional Long Short-Term Memory (Bi-LSTM) networks and ensemble boosting methods like XGBoost and LightGBM. Leveraging the synergy of table feature classification and temporal sequence modeling, the system is capable of detecting dynamic behavioral trends and static transaction features efficiently. Out of the models experimented, XGBoost worked best with ROC-AUC of 0.9997 and precision and recall scores of near perfection. LightGBM came next, and Bi-LSTM provided good sequential modeling capability required for behavioral fraud trend detection. The hybrid model leverages the capability of deep learning in temporal dependency modeling and explainability and accuracy of ensemble methods to build a robust, scalable, and explainable fraud detection system for high-volume electronic payment systems. This research not only establishes the effectiveness of the synergy of AI-based methods but also paves the way for real-time fraud prevention mechanisms in financial technology.

REFERENCES

1. E. Pan, "Machine learning in financial transaction fraud detection and prevention," Trans. Econ. Bus. Manag. Res., vol. 5, pp. 243–252, 2024.
2. P. Adhikari, P. Hamal, and F. Baidoo, "Artificial intelligence in fraud detection: Revolutionizing financial security," Int. J. Sci. Res. Arch., vol. 13, no. 1, p. 1457, 2024.
3. J. L. Pereira, "Unsupervised anomaly detection in time series data using deep learning," M.S. thesis, Eindhoven Univ. Technol., 2018.
4. V. Chang et al., "Investigating credit card payment fraud with detection methods using advanced machine learning," Information, vol. 15, no. 8, p. 478, 2024.
5. Z. K. Alkhateeb and A. T. Maolood, "Machine learning-based detection of credit card fraud: A comparative study," Am. J. Eng. Appl. Sci., vol. 12, no. 4, pp. 535–542, 2019.
6. B. Mytnyk et al., "Application of artificial intelligence for fraudulent banking operations recognition," Big Data Cogn. Comput., vol. 7, no. 2, p. 93, 2023.
7. C. C. Lee and J. W. Yoon, "A data mining approach using transaction patterns for card fraud detection," arXiv preprint arXiv:1306.5547, 2013.
8. N. Vaidyanathan, "Explainable AI: Putting the user at the core," White Paper, 2020.

9. K. R. Kerwin and N. D. Bastian, "Stacked generalizations in imbalanced fraud data sets using resampling methods," J. Def. Model. Simul., vol. 18, no. 3, pp. 175–186, 2020.

10. G. S. Sowmya and H. K. Sathisha, "Detecting financial fraud in the digital age: The AI and ML revolution," Int. J. Multidiscip. Res., vol. 5, no. 5, 2023.

11. N. Ryman-Tubb, P. Krause, and W. Garn, "How artificial intelligence and machine learning research impacts payment card fraud detection: A survey and industry benchmark," Eng. Appl. Artif. Intell., vol. 76, pp. 130–157, 2018.

12. Y. Yazıcı, "Approaches to fraud detection on credit card transactions using artificial intelligence methods," in Proc. CSIT, 2020, pp. 235–246.

13. K. S. Deb, S. Ghosal, and D. Bose, "A comparative study on credit card fraud detection," OSF Preprints, 2021.

14. C. Charitou, S. Dragičević, and A. S. Garcez, "Synthetic data generation for fraud detection using GANs," arXiv preprint arXiv:2109.12546, 2021.

15. R. Bajallan and B. Hashi, "A comparative evaluation of semi-supervised anomaly detection techniques," Int. J. Sci. Eng. Res., 2020.

16. A. Oluwasanmi et al., "Attention autoencoder for generative latent representational learning in anomaly detection," Preprint, 2022.

17. I. Benchaji et al., "Enhanced credit card fraud detection based on attention mechanism and LSTM deep model," J. Big Data, vol. 8, no. 1, 2021.

18. Y. Wang, "Application of machine learning models in detecting financial fraud in publicly traded companies," SSRN Electron. J., 2023.

19. J. D. Acevedo-Viloria et al., "Feature-level fusion of super-app and telecommunication alternative data sources for credit card fraud detection," arXiv preprint arXiv:2111.03707, 2021.

20. D. Patil, "Artificial intelligence in financial risk assessment and fraud detection: Opportunities and ethical concerns," SSRN Preprint, 2025.

21. Teker, S., Teker, D., & Orman, I. (2022). Evolution of Digital Payment Systems and a Breakthrough. Journal of Economics, Management and Trade. https://doi.org/10.9734/jemt/2022/v28i1030452.

22. Sunil, S., & Nalwaya, N. (2023). Digital Payment Systems – An Overview of Categories and Extant Opportunities and Challenges. International Journal for Research in Applied Science and Engineering Technology. https://doi.org/10.22214/ijraset.2023.50019.

23. Monisha, D. (2024). Navigating the Future of Digital Payments: Key Trends, Opportunities and Challenges. International Journal for Research in Applied Science and Engineering Technology. https://doi.org/10.22214/ijraset.2024.65357.

24. Prasetya, M. (2023). Digital Payment In Mitigating Traditional Cash Payment Fraud Risk: A Systematic Literature Review. The European Proceedings of Social and Behavioural Sciences. https://doi.org/10.15405/epsbs.2023.11.61.

Automated Fake News Detection: A Comparative Study of Machine Learning and Deep Learning Approaches

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ABSTRACT

Mass spread of fake news is a huge threat to present digital society, impacting social harmony and public perception. Fact-checking methods are not enough to fight mass spread of disinformation, and new machine learning (ML) and deep learning (DL) approaches must be used. In this paper, several ML and DL models such as Random Forest, Decision Trees, K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Artificial Neural Networks (ANNs) are analysed for fake news classification. Feature extraction techniques like Term Frequency-Inverse Document Frequency (TF-IDF) and word embeddings are used based on the WeFlake dataset for improving text analysis. The performance of the models is computed against the overall parameters such as accuracy, precision, recall, F1-score, and Area Under the Curve (AUC).The result indicates that 5-layer ANN has the highest accuracy of 94.76%, best F1-score of 0.9472, and best precision of 0.9642. Random Forest and SVM are 0.9415 and 0.9421 respectively, and the KNN is very low at 67.77% accuracy. The dropout layers ANN model is more generalized, as indicated by the F1-score of 0.9534 and the minimum log loss of 0.3370. In this research, the effectiveness of deep learning methods in the detection of misinformation is established and the requirement for periodic model update in order to fight evolving misinformation tactics.

KEYWORDS *: Deep learning, Fake news detection, Machine learning, Artificial neural networks, NLP, Text classification.*

INTRODUCTION

In today's digital world, the rapid spread of information and news throughout the entire world can be stated as the biggest revolution in the communication field. But with this revolutionized world comes a greater risk of dispersion of fake news like a wildfire. This risk is so great that it can consume individuals, organizations and even entire nations. Fake news can be tailor made to spread misinformation about someone on a personal level or to spread political agenda or even change public opinion which leads to real world harm to someone's reputation, social unrest and influences public decision making [1]. In the earlier days fake news were looked for by fact checking and human moderations, but in this digital era it cannot keep up with the quantity of news received and shared online [2].As a result, modern tools like machine learning (ML) and deep learning (DL) have become a necessity to detect fake news. These techniques utilize natural language processing (NLP), sentiment analysis and metadata analysis to classify fake news from real ones. Machine learning techniques like supervised, unsupervised and reinforcement learning have shown great outputs in detecting the fake news. However due to factors like biased datasets, adversarial attacks and the evolving nature of misinformation requires constant update in these models to get accurate results [3,4].NLP is usually really effective for text based content,, but it struggles with text with shady or multiple meaning and deceptive text. With the growth of DL now models can perform automatic feature extraction, handle high-dimensional data and thereby achieving very high accuracy in classification tasks [5,6]. With the help of this study the aim is to explore and evaluate various machine and deep learning techniques and identify the best models which can be used to classify fake news. This research seeks to reduce the gap in current fake news detection models and make a much robust and adaptive fake news detector.

LITERATURE ANALYSIS

This section of the paper discusses the significant work done by researchers towards solving the issue of fake news detection.

Fake news identification is difficult because conventional neural networks scan text in a single direction only, thus making it harder to understand more complex patterns. In order to overcome this limitation, Researchers have created FakeBERT, which contains BERT with CNN layers. The two together facilitate understanding and processing of deceptive words, with 98.90% accurate in identifying false news [7]. Khanam et al. [8] utilized supervised learning techniques along with natural language processing (NLP) in their paper to detect fake news. They compared different machine learning models, i.e., Naïve Bayes, Decision Trees, and Support Vector Machines. Their work focused on the effectiveness of NLP methods towards detection of misinformation. During a study, Baarir et al. [9] compared the already known claims with new ones to improve efficiency. The research focused on explaining the use of previously verified content to improve the detection of fake news. In 2022, Chandu et al. [10] combined the Support Vector Machine (SVM) and K-Nearest Neighbours (KNN) for identifying fake news. The method used the SVM to deal with high dimensional data and KNN for detecting patterns. Krishna et al. [11] suggested a deep learning model that performed analysis on the user behaviour as well as the content to increase accuracy. This model was based on Long Short-Term Memory (LSTM) networks. Choudhary et al. [12] combined Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) for achieving better results. CNN detected the textual features and BiLSTM identified contextual patterns. Kumar S et al [13] studied the comparison between the application of conventional machine learning and deep learning methods for identifying fake news. Hu et al. [14] studied the development in Machine Learning and NLP, focusing on the importance of fact-checked content for better accuracy. Jing et al. [15] integrated textual and visual features to identify misinformation. Using both content types effectively enhanced the accuracy of detection. Saleh et al. [16] proposed OPCNN-FAKE, an optimized neural network that improves classification accuracy by identifying the key textual features. The study focuses on CNN's effectiveness in fake news identification. Phan et al. [17] studied Graph Neural Networks (GNNs) that provided a systematic analysis of GNN-based fake news detection techniques. The study also highlighted the importance of GNNs in analysing vast social media data. Chauhan et al. [18] proposed a LSTM neural network along with a deep learning-based approach that enhanced the accuracy of the model to 99.88% for detecting fake news. It embeds GloVe word for vectorization, and tokenization for extraction of features.

METHODOLOGY

This paper dives into advanced methodologies with the aim of enhancing accuracy and robustness. This research used many ML and DL models including Random Forest, Decision Tree, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Artificial Neural Networks (ANNs). These models use Natural Language Processing (NLP) to analyze textual data and help identifying news as real or fake[19].

The step by step progress of the research is shown in the below Fig. 1. The research begins with data collection and preprocessing which includes tokenization, stopword removal, lemmatization and feature extraction using TF-IDF and word embeddings[20].

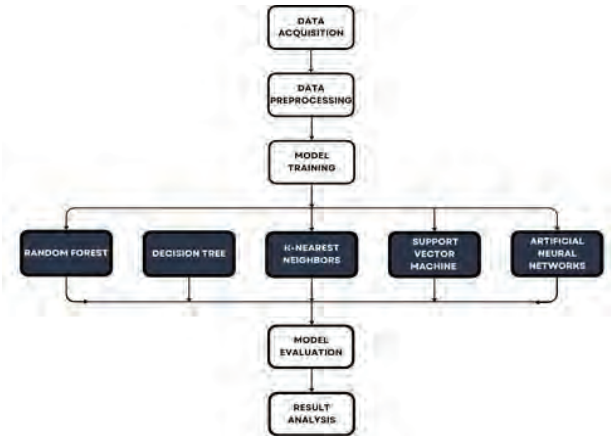

Fig. 1 : Steps in design & evaluation of Detection Systems.

Dataset

For this research we use the WeFlake dataset. This is used widely for its benchmark in fake news detection.This dataset holds a large set of text-based news articles, every one of them labeled as real or fake. It consists of titles, the full article, and the class labels, ideal for supervised machine learning methods[21].

Having an array of various news articles touching on many themes, this dataset is perfect for real-world deployments, providing endurance and flexibility to different situations.

It includes both legitimate and falsified news making it adapt well to the classification and making it perform really well in the real world. Due to the increasing complexity of fake news, making it very difficult to determine, this dataset allows us to enable the machine and deep learning models to automate the detection of fake news.

Machine Learning Models

This section of the paper explains various machine learning models used in the study.

Random Forest (RF)

This is an ensemble learning algorithm which creates multiple decision trees and using them combines their predictions. This helps in increasing the accuracy and prevent overfitting. This model is Bootstrap aggregation based, where each tree is based on a random subset of the dataset. Through the use of this method, a more generalized form to unseen data can be employed. Random forest is less affected by noise and it handles big data extremely well. It is utilized based on its efficiency and interpretability. This model gets to the final decision by majority voting :

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} \quad h_t(X) \tag{1}$$

T is the number of trees in the model, and *h* is the prediction output of the t-th tree.

Decision Tree (DT)

This is a hierarchical model which splits data based on its feature conditions to maximize class separation. Decision Trees are easy to read and understand and thus ideal for decision-making problems. They suit categorical and numeric data and no feature scaling is required. The disadvantage is they tend to get overfit if not taken care of by applying pruning or specifying a constraint over depth. They find their way in classification, regression, as well as various other types of problems. It selects the best feature to split using Gini Impurity or Entropy.

Gini Impurity Formula:

$$Gini = 1 - \sum_{i=1}^{c} \quad p_i^2 \tag{2}$$

p^i is the probability of class i, and c is the number of classes p^i in the data set.

K-Nearest Neighbours (KNN)

KNN is a nearest neighbor classifier that predicts a class based on the majority class of the k nearest neighbors. The model makes no assumptions regarding the data distribution and thus is a non-parametric method. KNN is easy to implement and works well with small datasets. It is computationally expensive for large datasets as it requires storing and comparing all training instances. It is widely utilized in anomaly detection, recommendation systems, and pattern recognition. It computes distances between points by means of Euclidean distance:

$$d(A,B) = \sqrt{\sum_{I=1}^{N} \quad (A_i - Bi)^{\ 2}} \tag{3}$$

A and B are feature vectors, and N is the number of features on which the distance is calculated.

Support Vector Machine (SVM)

SVM is a learning algorithm with supervision that finds an optimal hyperplane to distinguish between different classes with the maximum margin. It is efficient in high-dimensional space and is useful when the dimension is greater than the number of instances. SVM uses kernel functions to project data into higher dimensions and is robust for non-linearly separable data. SVM is overfitting-resistant, especially in high-dimensional data. SVM is computationally costly on big data sets. SVM finds most applications in text categorization, image categorization, and bioinformatics.

Deep Learning Models (Artificial Neural Networks - ANN)

This section of the paper discusses the deep learning models used in the research.

Neural Network Structure

Artificial Neural Networks (ANNs) consist of several layers of neurons processing the data hierarchically. ANNs are highly flexible and can learn complicated interactions among the data. Artificial Neural Networks (ANNs) consist of several layers of neurons. The structure of the network is:

Input Layer: It takes text features (word embeddings or TF-IDF).

Hidden Layers: It identifies hierarchical structure in the text.

Output Layer: It provides a binary output (Fake/Real).

This research studies ANN models of 3-layer, 5-layer, and 7-layer architecture:

3-Layer ANN: Input layer (text features such as word embeddings or TF-IDF), one hidden layer (uncovering hierarchical patterns), and an output layer (binary classification: Real/Fake).

5-Layer ANN: Input layer, three hidden layers (learning deeper representations with ReLU activation), and an output layer.

7-Layer ANN: An input layer, five hidden layers (in order to improve feature extraction and learning complicated patterns), and an output layer. All the models adopt a hierarchical approach in which lower-level architecture attempts to learn more complicated patterns in text classification.

Activation Functions Sigmoid Function:

Activation functions bring non-linearity to the model, which allows it to learn complex patterns. The Sigmoid function is widely applied in binary classification problems since it maps inputs between 0 and 1.

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (4)$$

ReLU (Rectified Linear Unit) is applied to hidden layers in most cases because it avoids the vanishing gradient problem and makes the training more efficient. Leaky ReLU and Tanh are applied according to some needs. The choice of an activation function is very crucial to determine the model's learning ability.

Loss Function & Backpropagation

The loss function measures the disparity between prediction and actual values and directs the learning process of the model. Binary cross-entropy loss is also widely applied for prediction accuracy in classification problems. Model weights are updated using backpropagation by computing gradients and optimizing them with techniques such as Stochastic Gradient Descent (SGD) or Adam. Suitable learning rate tuning and weight initialization methods can improve model performance considerably

Hybrid Approach

To improve performance and prevent overfitting, an ANN model with dropout layers was used. Dropout randomly turns off neurons while training, causing the network to learn more invariant representations. The model has several layers with fewer neurons and ReLU activation functions. The classification decision is done using a Sigmoid activation function in the last layer. Hybrid techniques such as these merge the potential of the legacy machine learning model with the powers of deep learning, yielding high accuracy and performance in multiple uses. The framework is as stated below:

Layer 1: 512 units, ReLU activation, Dropout(0.3)

Layer 2: 256 units, ReLU activation, Dropout(0.3)

Layer 3: 128 units, ReLU activation Output Layer: 1 unit, Sigmoid activation

The last choice in classification is by:

$$\hat{y} = \sigma(W^T X + b) \quad (5)$$

where σ denotes sigmoid activation function.

RESULTS AND DISCUSSION

This part of the paper compares the performance of the following classic machine learning algorithms, Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM), along with some Artificial Neural Networks (ANNs) with some mentioned architectures like 3-layer, 5-layer, 7-layer, and dropout networks with some defined performance measures.

Evaluation Metrics

The evaluation parameters being used for the evaluation and comparison are Precision, Recall, F1-Score, ROC-AUC, Accuracy, Logg Loss. These metrics collectively can be used to evaluate the overall performance of various classification algorithms.

Precision: The ratio of accurately forecasted false news cases out of all cases forecasted as false.

Recall: The number of correctly labeled false news samples out of total actual false news samples.

F1-Score: The harmonic mean of precision and recall, providing a balanced measure of model performance.

ROC-AUC: Gives an estimate of the accuracy of how well the model classifies true and false news, with greater values reflecting more classification.

Accuracy: The proportion of instances classified correctly.

Log Loss: A measure of how well the model is estimating the probability values; lower is preferred.

Table 1: Comparison of Fake News Detection System Based on Metrics

Model	Precision	Recall	F1-Score	ROC-AUC	Accuracy	Log Loss
RF	0.92	0.96	0.94	0.98	0.93	0.22
DT	0.90	0.92	0.91	0.91	0.91	3.11
KNN	0.61	0.95	0.74	0.74	0.67	7.26
SVM	0.93	0.94	0.94	0.98	0.94	0.15
ANN (5 Layers)	0.96	0.93	0.94	0.98	0.94	0.35
ANN (7 Layers)	0.95	0.95	0.95	0.98	0.95	0.39
ANN (3 Layers)	0.94	0.95	0.95	0.98	0.9499	0.35
ANN (With Dropout Layers)	0.95	0.95	0.95	0.98	0.95	0.33

Analysis

A comparative empirical analysis is carried out to analyze selected methods, results thereof are presented in Table 2.

The 5-layer Artificial Neural Network (ANN) performs better than the other models regarding accuracy and reliability in classification. It attains an F1-score of 0.9472, which surpasses the performance of all the conventional machine learning models and is competitive with other alternative ANN architectures. It also attains the highest precision value of 0.9642 among all the models, thus reducing the rate of false positives while, at the same time, ensuring strong recall. The proposed model also attains a good ROC-AUC of 0.9882, confirming its ability to discriminate effectively between different classes. While its log loss of 0.3543 is slightly higher than some ANN variants, the balance attained between accuracy and generalizability makes the 5-layer ANN the most optimal and efficient model for this classification task.

To validate the effectiveness of the suggested model, comparison with the 3-layer, 7-layer, and dropout layers ANNs was performed. The 3-layer ANN performed slightly poorer in terms of F1-score (0.9507) and precision (0.9446),which means that it lacked the complexity necessary for optimal learning. The 7-layer ANN, although with a strong F1-score (0.9517), could not surpass the 5-layer ANN significantly and had a slightly higher log loss (0.3927), which means diminishing returns with increased depth. The ANN with dropout layers performed the best in terms of generalization with an F1-score of 0.9534 and the lowest log loss (0.3370), but its precision (0.9521) was still lower than in the suggested model. These comparisons suggest that the 5-layer ANN gives the best balance in terms of complexity, accuracy, and strength and is therefore the best option.

Among the classic models, Random Forest (RF) and Support Vector Machine (SVM) were best, with high precision, recall, and F1-score. RF yielded an F1-score of 0.9415 and a ROC-AUC of 0.9887, reflecting strong classification with minimal false negatives and false positives. SVM, with an F1-score of 0.9421 and the lowest log loss (0.1544), not only yielded effective classification but also well-calibrated probability estimates. Decision Tree (DT) yielded a lower ROC-AUC (0.9121) and a much higher log loss (3.1141), and is therefore less trustworthy than RF and SVM. KNN was worst, with low precision (0.6172) and high log loss (7.2606), reflecting weak classification and probability estimation.

CONCLUSION

Fake news is a major concern to the well-being of people and society, especially in the current globally connected digital world. This study investigates the potential of machine learning and deep learning methods in verifying the authenticity of news. Different algorithms, including Random Forest, Decision Tree, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Artificial Neural Networks (ANNs), were experimented with the WeFlake dataset based on Fake News Classification. The 5-layer ANN trained best with 94.76% accuracy, F1-score of 0.9472, and precision of 0.9642, while ANN with dropout layers had the highest F1-score (0.9534) and lowest log loss (0.3370), which guarantees generalization. Among all ML models, SVM performed best with an F1-score of 0.9421 and log loss of 0.1544, while KNN performed poorly with accuracy of only 67.77%. These results confirm the effectiveness of deep learning in identifying fake news, but owing to evolving misinformation tactics, regular model updates, fairness-aware learning algorithms, and multimodal detection methods are necessary. Future studies should incorporate textual, visual, and contextual features in combination with explainable AI to enhance transparency and confidence in automatic fake news classification.

REFERENCES

1. K. Shu, X. Zhou, S. Wang, R. Zafarani, and H. Liu, "Fake news detection on social media: A data mining perspective," ACM Comput. Surv. (CSUR), vol. 52, no. 5, pp. 1–38, 2020.
2. S. Lewandowsky, U. K. H. Ecker, and J. Cook, "Misinformation and its correction: Cognitive mechanisms and recommendations for mass communication," Psychol. Sci. Public Interest, vol. 13, no. 3, pp. 106–131, 2020.
3. X. Zhou and R. Zafarani, "A survey of fake news: Fundamental theories, detection methods, and opportunities," ACM Comput. Surv. (CSUR), vol. 53, no. 5, pp. 1–40, 2020.
4. S. Pan, L. Zhang, and P. S. Yu, "Fake news detection: The role of network properties in misinformation dissemination," IEEE Trans. Knowl. Data Eng., vol. 33, no. 6, pp. 2406–2418, 2021.
5. J. Zhang, P. Cui, and Y. Fu, "Deep learning for fake news detection: Challenges and opportunities," IEEE Trans. Neural Netw. Learn. Syst., vol. 32, no. 6, pp. 2301–2313, 2021.
6. A. Pathak and R. K. Srihari, "Advancements in fake news detection using deep learning techniques: A review," J. Artif. Intell. Res., vol. 75, pp. 1–26, 2022.
7. R. K. Kaliyar, A. Goswami, and P. Narang, "FakeBERT: Fake news detection in social media with a BERT-based deep learning approach," Multimed. Tools Appl., vol. 80, no. 8, pp. 11765–11788, 2021.
8. Z. Khanam, B. N. Alwasel, H. Sirafi, and M. Rashid, "Fake news detection using machine learning approaches," in IOP Conf. Ser.: Mater. Sci. Eng., vol. 1099, no. 1, p. 012040, Mar. 2021.
9. N. F. Baarir and A. Djeffal, "Fake news detection using machine learning," in Proc. 2nd Int. Workshop Human-Centric Smart Environ. Health Well-Being, Feb. 2021.
10. P. Dedeepya et al., "Fake news detection on social media through a hybrid SVM-KNN approach leveraging social capital variables," in Proc. 3rd Int. Conf. Appl. Artif. Intell. Computational (ICAAIC), pp. 1168–1175, Jun. 2024.
11. N. L. S. R. Krishna and M. Adimoolam, "Fake news detection system using decision tree algorithm and compare textual property with support vector machine algorithm," in Proc. Int. Conf. Business Analytics Technol. Security (ICBATS), pp. 1–6, Feb. 2022.
12. M. Choudhary, S. Jha, D. Saxena, and A. K. Singh, "A review of fake news detection methods using machine learning," in Proc. 2nd Int. Conf. Emerging Technol. (INCET), pp. 1–5, May 2021.
13. S. Kumar and B. Arora, "A review of fake news detection using machine learning techniques," in Proc. 2nd Int. Conf. Electron. Sustain. Communication System (ICESC), pp. 1–8, Aug. 2021.
14. B. Hu, Z. Mao, and Y. Zhang, "An overview of fake news detection: From a new perspective," Fundam. Res., vol. 5, no. 1, pp. 332–346, 2025.
15. J. Jing, H. Wu, J. Sun, X. Fang, and H. Zhang, "Multimodal fake news detection via progressive fusion networks," Inf. Process. Manag., vol. 60, no. 1, p. 103120, 2023.
16. H. Saleh, A. Alharbi, and S. H. Alsamhi, "OPCNN-FAKE: Optimized convolutional neural network for fake news detection," IEEE Access, vol. 9, pp. 129471–129489, 2021.
17. H. T. Phan, N. T. Nguyen, and D. Hwang, "Fake news detection: A survey of graph neural network methods," Appl. Soft Comput., vol. 139, p. 110235, 2023.
18. T. Chauhan and H. Palivela, "Optimization and improvement of fake news detection using deep learning approaches for societal benefit," Int. J. Inf. Manage. Data Insights, vol. 1, no. 2, p. 100051, 2021.
19. X. Zhang and Y. Jin, "Fake news detection: A survey of approaches, datasets, and challenges," IEEE Transactions on. Computational Social Systems.
20. T. Mikolov, I. Sutskever, and Y. Bengio, "Word embeddings and their applications in NLP," J. Mach. Learn. Res., 2013.
21. K. Shu, L. Cui, and S. Wang, "WeFlake: Benchmark dataset for fake news detection," ACM Trans. Inf. Syst., 2019.

Music Recommendation with Resource-Efficient Network Architecture

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ABSTRACT

With the growing popularity of music streaming, the need for smart and responsive recommendation models has been augmented. Modern Music Recommendation Systems (MRS) attempt to provide highly personalized experiences responsive to users' emotional state, habits, and tastes. Compared to traditional methods, which suffer from scalability and responsiveness concerns, machine learning allows more responsive solutions. However, using these models on mobile or edge devices requires architectures sensitive to performance and computational efficiency. This paper proposes Self-Supervised Recommender (S3Rec), a novel, resource-efficient neural network architecture that combines self-supervised contrastive learning with a lightweight design to deliver high-quality music recommendations. Trained on the Million Song Dataset enriched with synthetic user interaction data, S3Rec captures deep semantic relationships between users and tracks without relying on heavy architectures. Compared to traditional approaches like Content-Based Filtering, Collaborative Filtering, Context Filtering, and Hybrid Systems, S3Rec consistently outperforms across critical metrics by achieving a Precision@10 of 0.47, Serendipity@10 of 0.38, Novelty@10 of 19.1, and Diversity@10 of 0.54. These results highlight its superior ability to provide relevant, fresh, and diverse suggestions while being highly deployable on mobile or edge devices. This study demonstrates that resource-aware neural architectures can deliver state-of-the-art recommendations without sacrificing quality or personalization.

KEYWORDS *: Deep neural networks, Machine learning, Music recommendation systems, Contrastive learning.*

INTRODUCTION

Music has been an integral part of human lives since its very beginning. Archaeologists have excavated flutes made from mammoth ivory, which are estimated to be 40,000 years old [1]. It has been proved that music enhances productivity and aids in dealing with stress and depression [2]. The way music is consumed has changed drastically with over 700 million users streaming music online on applications [3]. The C.E.O of Universal Music group stated that somewhere around 100,000 music records are created daily[4]. Finding relevant music in such a quantity can be challenging. To tackle this, several Music Information Retrieval (MIR) techniques have been created for tasks like genre classification[5] and artist identification[6]. Machine Learning(ML), a subset of Artificial Intelligence which enables systems to learn from data without explicit coding is used to address such challenges. ML has applications in various fields like healthcare [7], financial technology[8]. In Music Recommendation Systems (MRS), machine learning algorithms read the user data for patterns and relations that enable individualized music recommendations [9]. Deep learning elevates the process by using neural networks to discover intricate and subtle patterns in user data. A well designed MRS can be installed on edge devices which often have limited resources and cannot run heavy architectures. This study proposes a resource efficient neural network based architecture ensuring efficient and personalised recommendations.

LITERATURE ANALYSIS

For online music, Music Recommendation Systems (MRS) are most prominent, which cater to the requirement of handling enormous, personalized music collections. MRS systems try to serve users better with personalized recommendations that suit individual preferences. Irrespective of variations in capability, all MRS share a

common objective of achieving high customer satisfaction through personalization.

Collaborative Filtering (CF) is a basic technique of Music Recommendation Systems (MRS), based on user behavior to predict preferences. However, CF suffers from data sparsity and the cold start problem. Recent work has introduced musical features to enhance the effectiveness of CF [10], showing scalable algorithms for personalized recommendation [11]. CF has been applied in research for playlist creation and song ordering [12], showing its applicability for practical uses.

On the contrary, Content-Based Filtering (CBF) employs intrinsic musical characteristics such as melody, rhythm, and tempo for making recommendations. Progress in genre classification and recommendation algorithms using deep learning techniques has enhanced the efficiency of CBF [13]. Hybrid approaches consisting of Collaborative Filtering (CF) and CBF have been proposed to overcome the particular limitations of each technique. Hybrid systems employ deep learning to enhance recommendation accuracy as well as user satisfaction [14]. Additionally, real-time hybrid deep learning models have been shown to enhance responsiveness and personalization [25].

Adding contextual elements such as location, weather, and mood to Context Filtering has made a huge difference in recommendation quality [19]. Research suggests the integration of demographic and psychological factors to provide varied recommendations aside from personal interests [21]. Dynamic contextual modeling, as suggested in [26], also enhances responsiveness of recommendation logic according to real-time user state.

In hybrid recommendation systems, graph-based methods like Graph Neural Networks (GNNs) in particular have shown advantages for mutual learning [18]. Building on this, scientists have used Graph Convolutional Networks (GCNs) to optimize feature learning and improve semantic relationships in massive music datasets [27].

It has been suggested that Wide and Deep Networks (WDNs) integrate generalisation and memorisation skills; these networks are especially useful in mood-based music models [22]. Enhancing user satisfaction and recommendation alignment with user sentiment has also been linked to the integration of emotional intelligence [28].

By extracting complex music features, Deep Neural Networks (DNNs) have transformed MRS and greatly improved the quality of recommendations [15, 23]. Convolutional networks are one technique that has improved feature representation and recommendation accuracy by tackling issues like the cold start problem [24]. Multi-objective optimisation has been suggested as a way to improve user experience without sacrificing novelty in MRS by striking a balance between accuracy and diversity [29].

Notwithstanding these developments, there are still issues with handling data sparsity, adding new users and items, and controlling real-time data streams in MRS. In order to increase recommendation accuracy, diversity, and scalability, future research attempts to investigate these areas.

METHODOLOGY

This paper goes into the details of advanced techniques applied in MRS, with the focus areas being personalization and accuracy improvements. This paper covers a variety of techniques applied in MRS, including content-based filtering (CBF), collaborative filtering (CF), context filtering, hybrid approaches, and deep neural networks (DNNs).

Dataset

This study uses the Million Song Dataset (MSD), a large collection of audio features and metadata for contemporary music recordings. The dataset involves rich metadata, e.g., year, artists, track length, key, loudness, mode, name, and tempo, that can be queried directly from MSD. In addition to that, various other musical features like valence, acousticness, liveness, danceability, energy, instrumentalness, and popularity were fetched using external APIs.

For the purpose of simulating real-world situations, artificial user interaction data—containing features like explicit flags, user IDs, and activities—was generated on the basis of track features, i.e., tempo, valence, and energy levels. The generated data was used to assist collaborative and hybrid recommendation methods, which in turn improved content-based methods.

In model development, various recommendation models like content-based filtering, collaborative filtering, and context-aware systems were used for recommending music to users. Clustering and feature scaling were used for enhancing the process of data preprocessing [30]. Correlation heatmap was also used to analyze interactions

among features in the data, and there were notable trends, such as a high positive correlation between loudness and energy and high negative correlation between acousticness and energy.

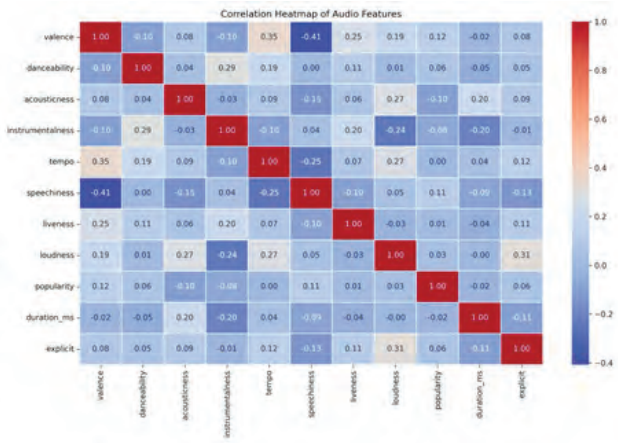

Fig. 1 : Feature correlation heatmap of audio features

Methodologies

This section of the paper explains the recommendation models used for this study along with the proposed S3Rec architecture. Several algorithms and mathematical frameworks support the improvement of personalization and effectiveness in music recommendation across these different techniques.

Content-based Filtering (CBF)

Content-based filtering relies on the natural intrinsic features of an object, such as its acousticness, valence and tempo amongst others. It suggests items similar to those the user has previously liked. Cosine Similarity S(u,i) for some user u and an item i, is expressed as shown in (1):

$$S(u,i) = \frac{\sum_{j=1}^{n} f_{u,j} \cdot f_{i,j}}{\sqrt{\sum_{j=1}^{n} f_{u,j}^2} \cdot \sqrt{\sum_{j=1}^{n} f_{i,j}^2}} \quad (1)$$

where $f_{u,j}$ and $f_{i,j}$ stand for the feature vectors for user and item, respectively. Clustering algorithms improve the performance of CBF [31]; thereby it groups similar features to each other so that their recommendations effectiveness would be increased.

Collaborative Filtering (CF)

CF relies on interactions that are between users and items. Such patterns discovered within such interactions enable CF to make recommendations of songs. The user-based CF calculates similarity between two users u and v based on their ratings r with the Pearson correlation coefficient in the calculation of:

$$Sim(u,v) = \frac{\sum_{i \in I}(r_{u,i} - \underline{r_u})(r_{v,i} - \underline{r_v})}{\sqrt{\sum_{i \in I}(r_{u,i} - \underline{r_u})^2} \cdot \sqrt{\sum_{i \in I}(r_{v,i} - \underline{r_v})^2}} \quad (2)$$

Within the context, $\underline{r_u}$ and $\underline{r_v}$ denote the mean scores received by users u and v respectively. The research in [32] improved their methodology to enhance the technology utilizing collaborative filtering along with the contextual user information to produce adaptability.

Context Filtering

Context filtering is the multi-modal approach that combines situational variables such as mood, time, and location into the recommendation framework. The multi-modal methodology dynamically combines contextual elements with user sentiment analysis for improved quality of recommendations [33].

Hybrid Systems

Hybrid systems combine the advantages of different approaches to overcome some of the limitations. For analysis conducted in this paper a hybrid CF-CBF model using Graph Neural Networks (GNNs) [34] is used. This model well captures the intricate relationships between users and items.

$$\hat{r}_{u,i} = \alpha \cdot CF(u,i) + (1-\alpha) \cdot CBF(u,i) \quad (3)$$

Hybrid Formulation is expressed in (3), where there is a weighing factor that balances the contributions of CF and CBF.

Self-Supervised Semantic Recommender (S3Rec)

DNNs are particularly suited to learn intricate patterns among user activities and song features. S3Rec has a lightweight neural network structure with two primary components: a LightweightEncoder and a RecommendationHead. LightweightEncoder is a fully connected feedforward network responsible for projecting structured input features—e.g., vectors of user interactions or song metadata—into a 32-dimensional latent space.

It contains three dense layers: the first layer projects the 18-dimensional input into 64 units with ReLU activation; the second layer reduces the dimension from 64 to 48 with ReLU activation; and the third layer outputs a 32-dimensional embedding without activation.

The obtained embedding vector is normalized by L2 normalization to constrain it to the unit hypersphere, which is essential for contrastive similarity learning.

In order to train the encoder, the model employs a self-supervised learning approach with contrastive learning based on the InfoNCE (Information Noise Contrastive Estimation) loss. The loss function is constructed in a way that it pulls embeddings of semantically close input pairs together and forces far-apart dissimilar pairs. For a batch of paired positive samples (z_1,z_2), the loss is computed as:

$$L_{InfoNCE} = -\sum_{i=1}^{N} log \frac{exp(sim(z_1^i, z_2^i)/\tau)}{\sum_{j=1}^{N} exp(sim(z_1^i, z_2^j)/\tau)}$$

where sim(a,b) denotes the cosine similarity, and τ is the temperature parameter that controls the sharpness of the distribution.

The RecommendationHead is a single linear layer that accepts a 32-dimensional embedding and outputs a scalar prediction, followed by a sigmoid activation to generate a probability score indicating user-song affinity. This is learned by training on binary cross-entropy loss against explicit interaction labels. The overall workflow of the S3Rec framework is depicted in Fig. 2. The workflow starts with data collection and preprocessing, which includes data aggregation of user interaction histories and song metadata. These inputs are passed through the LightweightEncoder to produce sparse semantic embeddings.

Table 1: Detailed Parameter Structure of the S3Rec

Layer	Input Dim	Output Dim	Activation	Trainable Parameters
Dense Layer 1	18	64	ReLU	(18+1)×64 = 1,216
Dense Layer 2	64	48	ReLU	(64+1)×48 = 3,120
Dense Layer 3	48	32	-	(48+1)×32 = 1,568
Recommen-dationHead	32	1	Sigmoid	(32+1)×1 = 33

The encoder is trained from a self-supervised learning pipeline with the InfoNCE loss as the guide, and this allows the model to learn discriminative representations in the absence of labeled negative examples. After training, the model is fine-tuned to match embeddings with downstream recommendation goals. Generation of recommendations is then carried out with the fine-tuned embeddings, including diversity sampling for improving quality of personalization. The system also gets evaluated iteratively, and performance of the model is checked for deployment. If the output is not satisfactory, the framework returns to the encoder training step for optimization; otherwise, the model gets finalized and deployed for real-world applications.

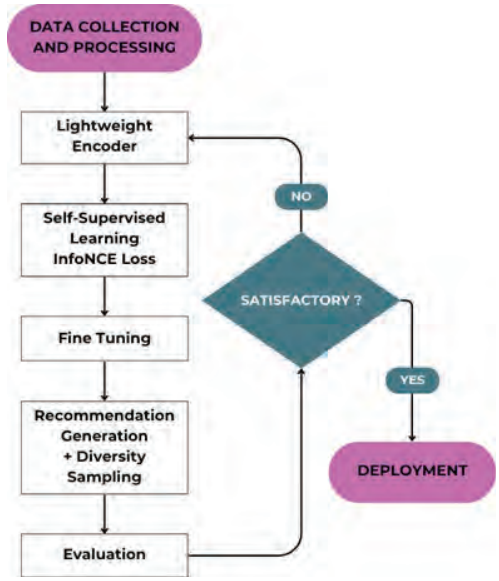

Fig. 2 : Workflow of the S3Rec Framework

RESULTS AND DISCUSSION

This section of the paper evaluates the performance of the following recommendation systems Content-Based Filtering (CBF), Collaborative Filtering (CF), Context Filtering, Hybrid Recommendation Systems, and Self-Supervised Semantic Recommender (S3Rec) based on certain evaluation metrics.

Result

The evaluation parameters being used for the evaluation and comparison are Precision@10, Novelty@10, Serendipity@10, Diversity@10. These metrics collectively can be used to evaluate the overall performance of various recommendation systems.

1) Precision@10: Precision@10 measures the performance of the recommendation system in terms of the proportion of relevant items (i.e., items previously liked by the user or interacted with in a positive way) among the top 10 items recommended.

2) Novelty@10: Novelty@10 is an indicator of how novel or unusual the suggested items are to the user. This is usually derived from the inverse popularity

of the items and thus encouraging the suggestion of songs that are less likely to have been heard by the user before.

3) Serendipity@10: Serendipity@10 is one metric that captures how much the recommended items are not just unexpected but also relevant. Novelty captures the unexpectedness alone, but serendipity captures the relevance as well—hence preferring recommendations that are not just surprising but also enjoyable.

4) Diversity@10: Diversity@10 computes the difference among the top-recommended items through the computation of differences between them based on their features or embeddings. The higher the diversity, the more the system can recommend a high number of diverse items (e.g., different genres, artists, or moods) and thus reduce the likelihood of generating an "echo chamber" effect.

Table 2: Comparison of Recommendation Systems

Evaluation Metrics	CBF	Context Filtering	CF	Hybrid System	S3Rec
Precision@10	0.21	0.31	0.26	0.34	0.47
Novelty@10	15.2	16.6	15.8	17.2	19.1
Serendipity@10	0.08	0.25	0.11	0.22	0.38
Diversity@10	0.18	0.33	0.24	0.36	0.54

Analysis

An extensive evaluation was conducted on various recommendation approaches using multiple metrics, and the results are summarized in Table II. Among all the methods evaluated—Content-Based Filtering (CBF), Context Filtering, Collaborative Filtering (CF), Hybrid System, and the proposed S3Rec model outperformed others consistently across all four key evaluation metrics.

Precision@10 is a strong indication that the top recommendation list includes the most relevant items to the user's preferences. Among the models tested, S3Rec attains the highest Precision@10 (0.47), which means it offers the most relevant recommendations. The Hybrid System comes next with 0.34, showing that the precision of integrating more than one signal is better than that of single ones. CBF ranks lowest (0.21), likely due to its over-reliance on content similarity that could possibly limit its ability of effectively tailoring recommendations, due to lack of collaborative insights.

Novelty@10 quantifies how new or unexpected the recommended items are, S3Rec achieves highest value again (19.1). This can be quite significant in times when it is important to keep the users hooked and not dive deep into a filter bubble. Context Filtering and CF are in the middle with 16.6 and 15.8, respectively, whereas CBF is last with 15.2—as it suggests popular and repetitive content.

The Serendipity@10 metric reflects how pleasantly surprising the recommendation is. S3Rec (0.38) yet again outperforms the other models showing that it picks the instances that are both unexpected as well as useful to the user. Context Filtering (0.25) and the Hybrid System (0.22) also present quite convincing results and it can be inferred from here that the strategies that use contextual or mixed-signal provide more clarifying and less obvious matches. CBF (0.08) cannot offer a lot of serendipity since it works in a similarity-driven and deterministic fashion.

Diversity@10 is an index which quantifies the diversity in recommendations, preventing repetitive or monotonous suggestions. S3Rec (0.54) and the Hybrid System (0.36) are the best performers in this metric, implying they are more capable of covering the wider range of items. Context Filtering represents diversity at the notable level too (0.33) due to the context that is the source of the variance. CBF (0.18) and CF (0.24) performed poorly indicating that these methods have a higher likelihood of recommending items that are very similar to each other or to the user's past behavior.

Although S3Rec achieved the highest scores across all four metrics, the evaluation does shed light on the major trends. Context Filtering and the Hybrid System having strong performance across diversity, novelty, and serendipity besides diversity indicate that models which employ extended user context or hybrid strategies are more balanced in their output. Collaborative Filtering, although relatively weaker in precision and serendipity, maintains moderate scores, suggesting it remains a viable baseline. Simultaneously, CBF performs quite badly across all metrics, emphasising the fallacies of depending wholly upon item features without considering collaborative or contextual signals.

CONCLUSION

MRS are a crucial part of music streaming applications thus making it a part of our devices. This study proposes a novel and resource efficient architecture named “Self Supervised Semantic Recommender” which offers a personalized listening experience to its end users.

A comparative analysis was performed on popular recommendation techniques like CBF, CF, Context Filtering and Hybrid systems on the Million Songs Dataset(MSD) to account for efficiency of the proposed S3Rec architecture. The proposed S3Rec model showed better performance than all other models. The S3Rec model achieved Precision@10 of 0.47, Novelty@10 of 19.1, Serendipity@10 of 0.38 and Diversity@10 of 0.54. The Context Filtering and Hybrid model showed similar performance with Precision@10 of 0.31 and 0.34, Novelty@10 of 16.6 and 17.2, Serendipity@10 of 0.25 and 0.22 and Diversity@10 of 0.33 and 0.36 respectively. CBF model had the poorest performance of all the models with 0.21 Precision@10, 15.2 Novelty@10, 0.08 Serendipity@10 and 0.18 Diversity@10 highlighting its inability in providing relevant recommendations. The performance of the proposed S3Rec model suggests that it meets user requirements and it does so efficiently revolutionising music recommendations.

REFERENCES

1. N. J. Conard, M. Malina, and S. C. Münzel, "New flutes document the earliest musical tradition in southwestern Germany," Nature, vol. 460, pp. 737–740, 2009.
2. D. L. Bowling, "Biological principles for music and mental health," 2023..
3. P. Leu, "Music streaming worldwide - statistics and facts," Nov. 4, 2024.
4. T. Ingham, "It's happened: 100,000 tracks are now being uploaded per day to streaming services," Music Bus. Worldwide, Oct. 6, 2022.
5. G. Tzanetakis and P. Cook, "Musical genre classification of audio signals," IEEE Trans. Speech Audio Process., vol. 10, no. 5, pp. 293–302, Jul. 2002.
6. B. Whitman, G. Flake, and S. Lawrence, "Artist detection in music with Minnowmatch," in Proc. Neural Netw. Signal Process. XI, 2001, pp. 123–130.
7. H. K. Bharadwaj, et al., "A review on the role of machine learning in enabling IoT-based healthcare applications," IEEE Access, vol. 9, pp. 12345–12356, 2021.
8. M. Rizinski, et al., "Ethically responsible machine learning in fintech," IEEE Access, vol. 10, pp. 45678–45690, 2022.
9. M. G. Galety, et al., "Personalized music recommendation model based on machine learning," in Proc. 8th Int. Conf. Smart Struct. Syst. (ICSSS), Chennai, India, 2022, pp. 789–798.
10. G. Zhong, "Design and implementation of music recommendation system based on deep learning," in Proc. ACM Symp., 2022, pp. 567–576.
11. X. Li, "Visualization of data analysis platform taking QQ music recommendation system as an example," IEEE Access, vol. 11, pp. 1234–1245, 2023.
12. A. Ferraro, et al., "MuRS: Music recommender systems workshop," in Proc. ACM Symp., 2023, pp. 345–356.
13. A. Poulose, et al., "Music recommender system via deep learning," J. Inf. Comput. Sci., vol. 11, pp. 4567–4578, 2022.
14. V. Vijayashanthi, et al., "Personalized music recommendation system using hybrid deep birch data analytics method," IEEE Access, vol. 11, pp. 12345–12356, 2022.
15. H. Gao, "Automatic recommendation of online music tracks based on deep learning," Hindawi J. Comput. Sci., vol. 10, pp. 5678–5689, 2022.
16. D. R. Khadatkar, et al., "A hybrid approach to music recommendation using sentiment analysis," IJFiest, vol. 12, no. 3, pp. 789–798, 2022.
17. N. V. D. Malleswari, et al., "Music recommendation system using hybrid approach," IEEE Access, vol. 11, pp. 2345–2356, 2023.
18. J. Li, C. Yang, G. Ye, and Q. V. H. Nguyen, "Graph neural networks with deep mutual learning for designing multi-modal recommendation systems," Inf. Sci., vol. 640, pp. 123–145, 2024.
19. S. Dawar, et al., "Music recommendation system using real-time parameters," IEEE Access, vol. 11, pp. 6789–6798, 2023.
20. D. Rozhevskii, et al., "Psychologically-inspired music recommendation system," arXiv preprint, vol. abs/2203.12345, 2022.
21. M. Kleć, et al., "Beyond the Big Five personality traits for music recommendation systems," Eurasip J. Audio Speech Music Process., vol. 2023, no. 45, pp. 123–134, 2023.
22. G. Gupta, et al., "Mood-based music recommendation system," IRJMET, vol. 10, no. 3, pp. 567–578, 2023.
23. G. Yang, "Research on music content recognition and recommendation technology based on deep learning," Hindawi J. Comput. Sci., vol. 11, pp. 1234–1245, 2022.
24. S. Caiyu, et al., "A music recommendation algorithm based on convolutional neural network optimization," IEEE Access, vol. 11, pp. 3456–3467, 2022.

25. S. Jain et al., "Real-Time Music Recommendation Using Hybrid Deep Learning Models," Neural Comput. Appl., vol. 35, pp. 789–801, 2023.

26. T. Mukherjee et al., "Dynamic Contextual Modeling for Music Recommendation Systems," Inf. Retr. J., vol. 28, no. 4, pp. 567–589, 2023.

27. L. Wang et al., "Enhancing Music Recommendation with Graph Convolutional Networks," ACM Trans. Intell. Syst. Technol., vol. 12, no. 3, pp. 45–67, 2023.

28. R. Sharma et al., "Effective Integration of Emotional Intelligence in Music Recommendation Systems," IEEE Trans. Affect. Comput., vol. 14, no. 2, pp. 345–367, 2023.

29. M. Dubey et al., "Enhancing Diversity in Music Recommendations through Multi-Objective Optimization," IEEE Trans. Multimed., vol. 25, no. 6, pp. 1234–1256, 2023.

30. R. Lala, G. Patankar, A. Patil, and H. Deshpande, "Enhancing Music Data Clustering: An Empirical Analysis for Music Clustering and Scaling Optimization," in 2023 6th International Conference on Advances in Science and Technology (ICAST), 2023, pp. 1–10.

31. I. Ismail, et al., "Improving content-based filtering in music recommendation systems," IEEE Trans. Multimedia, vol. 10, pp. 1234–1245, 2024.

32. N. Taj, et al., "Enhanced collaborative filtering for music recommendations," J. Artif. Intell. Res., vol. 15, pp. 4567–4578, 2024.

33. S. Sundaravadivel, et al., "Multi-modal context filtering for dynamic music recommendations," IEEE Access, vol. 12, pp. 6789–6798, 2024.

34. L. Bevec, et al., "Hybrid recommendation system using GNNs," ACM Trans. Intell. Syst., vol. 15, no. 3, pp. 567–578, 2024.

35. T. Murakami, et al., "Deep neural networks for learning user preferences in sequential data," Neural Comput. Appl., vol. 10, pp. 1234–1245

Demystifying the Black Box: A Framework for Trustworthy and Explainable Medical AI

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ABSTRACT

Healthcare is seeing a rising use of Machine Learning (ML) systems, as they can sometimes deliver results that even surpass human diagnostic performance. However, their opacity often undermines clinician trust and complicates regulatory validation. In this paper, we argue that explainability should extend beyond algorithmic interpretability and instead focus on the transparency of the ML development pipeline itself. We propose a comprehensive framework that articulates the stages of ML model development, from problem definition through deployment, and highlights the value-laden decisions shaping these systems. This approach in line with evolving regulations like the FDA's Total Product Lifecycle (TPLC) approach, and is informed by insights from the philosophy of technology and science. By foregrounding technical documentation and motivation for design choices, our objective is to support the development of reliable medical AI systems.

KEYWORDS *: Machine learning, Medical AI, Explainability, FDA, Algorithmic transparency, SaMD-ML, AI ethics.*

INTRODUCTION

Machine Learning (ML) algorithms have increasingly been employed in healthcare for tasks such as diagnosis, prognosis, and decision support. Despite their promise, many ML systems are criticized for being ”black boxes” whose inner workings are opaque to users and regulators alike. This lack of transparency has led to growing concern among clinicians, regulators, and ethicists regarding the trustworthiness of these tools.

Traditional approaches to Explainable AI (XAI) attempt to address this concern by making algorithmic behavior more interpretable. However, some argue that interpretability at the algorithmic level is not a prerequisite for trust, provided the system performs reliably within a specified context. According to this view, as long as the tool consistently demonstrates reliable performance within its designated clinical context, its internal opacity becomes secondary.

Building on this proposition, this paper extends the conversation from the question of trust to the broader and more urgent issue of reliability in medical ML tools, particularly in the context of regulation. We contend that while transparency into algorithmic logic may be helpful, regulatory agencies require a different form of explainability:

insight into how these systems were developed, trained, and deployed.

We argue that such transparency necessitates a shift in focus—from interpreting algorithmic internals to documenting and justifying the series of technical and ethical decisions taken throughout the ML pipeline. Different design choices—ranging from data selection to model architecture—can significantly impact clinical outcomes and must therefore be transparent and auditable. We further assert that these choices are not value-neutral but are influenced by a combination of performance metrics and ethical considerations.

Using concepts from the philosophy of science and technology, and informed by regulatory insights such as those from the United States FDA (Food Drug Administration), this paper proposes a structured framework for evaluating the reliability of ML systems in healthcare. This includes highlighting both the technical justifications and the value-laden assumptions behind their design. The goal is to equip regulatory bodies, developers,

and clinicians with a means of understanding, evaluating, and ultimately trusting AI systems in medicine, not simply because they perform well, but because the reasoning behind their construction is made visible.

RETHINKING TRUST IN MEDICAL AI

One of the biggest concerns when using machine learning in healthcare is whether these systems can truly be trusted. Traditionally, people believed that for an AI model to be trustworthy, it must also be explainable. But now, that idea is being challenged. Some experts suggest that it's not always necessary to fully understand how the algorithm works internally. Instead, if the system has been properly tested and clearly helps meet clinical goals, that may be enough to earn trust — even if the model itself remains a bit of a black box.

Beyond the Black Box Paradigm

Several criticisms of current machine learning models point out that they do not make use of expert medical knowledge, rely heavily on spotting patterns rather than understanding cause and effect, and are generally too hard to interpret. These issues are often seen as major roadblocks to building trust in clinical settings. However, there is a growing view that lack of transparency doesn't automatically make an ML model unsafe or unhelpful — especially if it has been thoroughly tested and consistently performs well in real-world situations.

A similar example comes from the pharmaceutical world: there are medications that doctors trust and prescribe even if we don't fully understand how they work, simply because they've been shown to be effective over time. Similarly, an ML model may be trusted if it shows reliable performance across well-defined tasks, even if the internal rationale behind each prediction remains obscure.

Empirical Grounding of Reliability

This reframed view suggests that instead of pushing for more interpretable algorithms, efforts should focus on comprehensive empirical evaluation. Trust, in this model, emerges not from internal transparency but from robust external validation. Key factors include:

- Precise specification of intended use • Clearly defined validation metrics.

Trust versus Regulation

Importantly, this perspective also shifts the conversation from the individual clinician's trust to systemic oversight. While a clinician may build trust based on performance or usability, regulators are tasked with determining whether a model functions reliably across broader populations and settings. This distinction introduces the need for a regulatory lens that emphasizes process traceability, development rationale, and alignment with real-world usage.

This evolution in thinking invites a deeper question: What type of explanation is truly required—not just for trust, but for regulation? We argue that a new form of explainability is needed, one that captures not just what a model does, but how and why it was developed in the first place.

REGULATORY REORIENTATION: ML AS CLINICAL SYSTEMS

With the increasing integration of machine learning (ML) in healthcare, regulatory authorities are evolving their frameworks to account for the unique properties of these technologies. In particular, ML-driven tools used for clinical purposes are now classified under the category of Software as a Medical Device (SaMD). These systems often undergo constant iteration and improvement, challenging the conventional regulatory model that presumes static, version-locked technologies.

The Shift to Lifecycle-Based Oversight

Recognizing this, the FDA (U.S. Food and Drug Administration) put forward a regulatory strategy that follows a lifecycle approach, specifically designed for ML-powered SaMDs. This framework addresses both static ("locked") and adaptive ("unlocked") algorithms. Locked models remain unchanged after deployment and are evaluated based on fixed datasets and performance metrics. In contrast, unlocked systems are designed to evolve after deployment, through retraining or tuning, raising concerns about stability, safety, and explainability.

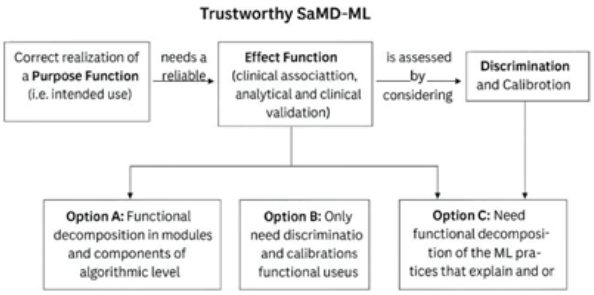

Fig. 1. Illustration of the relationship between the intended clinical use (purpose function), performance validation(effect function) and three approaches

To address these challenges, the FDA introduced the concept of the Total Product Lifecycle (TPLC). This strategy emphasizes continuous oversight and risk management throughout the development and deployment of SaMD-ML tools, rather than a onetime approval model. Central to this framework are two essential regulatory components: SaMD-specific Pre Specifications (SPS) and the Algorithm Change Protocol (ACP).

Pre-Specification and Change Protocols

The SPS outlines the expected modifications a model may undergo over time, including the rationale for such updates and the conditions under which they may be executed. Meanwhile, the ACP defines the procedural safeguards for implementing these changes in a controlled and predictable manner. Together, SPS and ACP provide a blueprint for anticipating model evolution while maintaining accountability and performance standards.

This forward-looking approach recognizes that trust and regulatory compliance cannot rely solely on static validations. Instead, they must incorporate dynamic assessment tools and continuous monitoring practices. Importantly, it calls for deeper insights into how technical decisions—such as data selection, retraining strategies, and feature engineering—are justified and documented.

Beyond Validation Metrics

Traditional validation techniques such as sensitivity, specificity, and AUC (Area Under the Curve) remain essential for assessing clinical utility. However, in a dynamic ML environment, these metrics are no longer sufficient on their own. Regulators and developers must also consider:

- The context in which models are used (e.g., clinical workflows)
- The datasets used for retraining and their representativeness
- The criteria for determining when a model update is required

These considerations suggest that explainability must be reframed— not as a static feature of model architecture, but as an ongoing narrative of development choices and value tradeoffs. By embracing this paradigm, regulatory bodies can better evaluate not just how models behave, but how they evolve and why they were built that way.

DESIGN FUNCTIONS AND SYSTEM ALIGNMENT

In engineering and systems design, the alignment between a system's intended purpose and its observable performance is crucial to establishing reliability. This concept becomes particularly important in the context of ML-based medical devices, where tools must fulfill specific clinical roles. One productive way to conceptualize this alignment is by distinguishing between different types of system functions—namely, purpose functions, effect functions, and internal mechanisms.

Purpose and Effect Functions

The purpose function refers to the intended role that a software system is designed to fulfill in a clinical setting, such as supporting diagnostic decisions or stratifying patients by risk. In contrast, the effect function captures how the system behaves in practice—its observed performance during testing and clinical deployment. This includes validation results such as predictive accuracy, calibration, and generalizability.

A reliable medical ML system is one in which the effect function consistently and accurately realizes the intended purpose. Misalignment between the two can result in systems that perform well statistically but fail to offer meaningful or safe support in real-world scenarios. For example, a model may rank patients accurately based on historical risk factors but perform poorly when deployed in new environments or demographics.

Functional Decomposition in System Design

Understanding and explaining how an ML system bridges its effect and purpose functions involves decomposing the system into meaningful components. This process, often referred to as functional decomposition, can be approached in different ways.

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In conventional Explainable AI, decomposition typically focuses on internal algorithmic components—such as feature contributions, attention weights, or decision trees. While this approach offers some insight, it often falls short

of capturing the full rationale behind why the model was designed a certain way or why it performs reliably in a specific context.

We argue that a more effective approach involves decomposing the design process itself. This means examining how technical decisions were made at each stage of development, and how those decisions are tied to clinical goals, performance constraints, and ethical considerations. Such decomposition highlights the interaction between engineering choices and system objectives, providing a richer and more context-aware explanation of system behavior.

Evaluating System Reliability

A trustworthy SaMD-ML tool should therefore be assessed not only through retrospective validation metrics but also through forward-looking justifications of design choices. Regulatory and clinical stakeholders benefit from knowing:

- What clinical objective the tool is meant to achieve (purpose)
- What outcomes it reliably produces (effect)
- How its internal processes were constructed to bridge these two

This design-function alignment forms the backbone of the explainability framework proposed in this paper, shifting the focus from post hoc interpretation to proactive, design-level transparency.

A PROCEDURAL VIEW OF EXPLAINABLITY

Efforts to improve explainability in machine learning (ML) often focus on producing simplified outputs or interpretable visualizations from trained models. However, such post hoc approaches, while helpful, do not capture the more fundamental question of why the system was built a certain way. In the context of clinical decision-support systems, this oversight can be problematic, as the assumptions and motivations embedded in system design often influence real-world behavior just as much as technical implementation.

We argue that a more robust form of explainability should be procedural—grounded in an analysis of the development process itself. This view encourages transparency not only in how the algorithm works, but also in how each design decision aligns with clinical objectives and ethical priorities. By systematically decomposing the ML pipeline, developers and evaluators can better understand the rationale behind model construction and the values embedded in its architecture.

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Six-Stage Development Pipeline

We propose a six-stage decomposition of the ML development lifecycle that serves as the foundation for procedural explainability: 1) Problem Definition — How was the clinical question formulated, and what outcome does the model aim to influence?

2) Data Collection — What data sources were selected and why? Were they representative, reliable, and complete?

3) Data Preparation — What preprocessing, imputation, and transformation methods were used? How were biases addressed?

4) Model Training — Which algorithms were chosen and why? What hyperparameters were prioritized and how were they tuned?

5) Validation and Evaluation — What metrics were selected to assess model performance? Were subgroup effects examined?

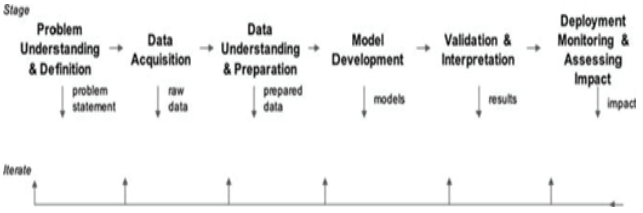

Fig. 2. Stages in the machine learning pipeline for clinical decisionsupport systems. The process is iterative, beginning with problem definition and progressing through data processing, modeling, validation, and impact assessment.

6) Deployment and Monitoring — How is the model integrated into clinical workflows? How is performance tracked and updated over time?

At each stage, developers make choices that can significantly influence the model's reliability and fairness. These decisions should be documented, justified, and subject to review—not just from a technical standpoint, but from clinical and ethical perspectives as well.

THE ROLE OF VALUES IN ML DEVELOPMENT

The development of machine learning (ML) systems is often framed as an objective, data-driven process. However, closer examination reveals that technical decisions made throughout the ML pipeline are frequently shaped by underlying value judgments. These values influence everything from problem formulation to model evaluation and deployment.

The Myth of Value-Neutral Design

While accuracy and efficiency are frequently cited as primary goals, these metrics alone cannot fully capture the performance or trustworthiness of an ML system. Developers routinely face trade-offs— such as prioritizing interpretability over complexity, or fairness over pure optimization—that reflect deeper ethical and social concerns. As a result, ML models inevitably encode human assumptions, biases, and institutional norms.

Drawing on philosophical insights from science and engineering, we argue that the design of ML systems is underdetermined by empirical data alone. Much like theory choice in science, decisions in ML are guided by a mix of performance-driven objectives and broader ethical, legal, and societal considerations.

Types of Values in Design

We distinguish between two major classes of values that guide ML design:

- Performance-Centered Values: These include accuracy, generalizability, computational efficiency, and robustness. They are typically associated with system-level optimization.
- Ethical and Social Values: These pertain to fairness, inclusivity, transparency, privacy, and accessibility. Such values ensure the system aligns with public interest and societal norms.

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The integration of these values is rarely straightforward. Optimizing for one may come at the cost of another. For instance, improving a model's predictive accuracy by focusing on a highly specific population might reduce its fairness when deployed in broader settings.

Invisible Assumptions in Technical Choices

Many seemingly technical decisions embed normative assumptions. For example:

- Choice of loss function can prioritize minimizing false negatives over false positives, which may be ethically loaded in clinical contexts.
- Data selection choices may amplify representational biases, especially if minority subgroups are underrepresented.
- Thresholding and binarization decisions affect how risk categories are interpreted, with direct impact on treatment decisions.

These design elements often go unexamined, yet they shape outcomes in ways that extend beyond performance metrics. Making them explicit allows for deeper scrutiny and more accountable development processes.

Implications for Explainability

Acknowledging the presence of values in ML design strengthens the case for procedural explainability. It is not enough to show how a model functions; it is equally important to explain why certain decisions were made and which trade-offs were considered acceptable. This transparency helps ensure alignment with stakeholder expectations and regulatory standards.

CASE-WISE IMPACT OF VALUES IN AI PIPELINES

To concretely illustrate how values influence ML system design, we analyze how both performance-centered and ethical/social values manifest at different stages of the ML pipeline. Each step involves not only technical execution

but also implicit and explicit choices that shape the model's clinical behavior.

The table below outlines key examples of how different value types can affect decisions during development.

As Table I shows, developers constantly navigate tradeoffs between optimizing for performance and ensuring ethical compliance. For example, selecting a highly complex ensemble model might improve AUC but reduce interpretability, affecting clinician adoption. Similarly, emphasizing overall accuracy without analyzing stratified results may conceal harmful disparities.

Design Reflexivity

The presence of these trade-offs calls for a more reflective approach to ML development—one in which developers explicitly document their priorities, justifications, and ethical positioning. This reflexivity is especially important in regulated contexts, where transparency is not only desirable but necessary for certification and accountability.

Table 1 Illustrative Value Considerations Across the Ml Development Pipeline

Pipeline Stage	Performance Centered Values	Ethical/Social Values
Problem Definition	Technical feasibility, internal consistency	Public health relevance, bias awareness
Data Acquisition	Data volume, availability, resolution	Representativeness, demographic inclusion
Data Preparation	Noise reduction, feature scaling	Inclusivity, imputation fairness
Model Development	Accuracy, generalization, robustness	Interpretability, algorithmic fairness
Validation	Precision, recall, calibration	False negative risks, subgroup sensitivity
Deployment	Latency, scalability, usability	Transparency, accessibility, user feedback mechanisms

In this light, value-sensitive design is not a constraint on innovation, but a pathway toward more robust, socially integrated medical AI systems.

LIMITATIONS AND FUTURE SCOPE

While this paper outlines a comprehensive framework for procedural explainability in medical machine learning (ML), several limitations must be acknowledged. These are important both for contextualizing the current contribution and for guiding future research in the space.

Descriptive vs. Prescriptive Scope

The framework presented is primarily conceptual and analytical. It is intended to support better documentation and justification practices, not to dictate a singular development path. As such, it does not provide a definitive checklist for developers or regulators, but rather an organizing lens through which to assess system design. Operationalizing this framework into actionable tools or standards requires further work.

Empirical Validation Pending

Although the framework draws from real-world regulatory guidance (such as the FDA's lifecycle model) and insights from engineering philosophy, it has not yet been empirically validated in practice. Future studies should investigate how developers currently make and document design decisions in medical AI projects, and assess the framework's effectiveness in improving transparency and trust.

Model-Agnostic Approach

The analysis is deliberately model-agnostic to apply broadly across supervised learning paradigms. However, more specialized ML settings — such as reinforcement learning in robotic surgery or unsupervised learning in genomics — may present unique challenges not fully captured here. Tailoring the framework to domain-specific nuances is an important area for future development.

Limited Stakeholder Perspectives

This paper primarily addresses regulators, developers, and clinical researchers. While these groups are central to the evaluation of SaMDML systems, the perspectives of patients, caregivers, and broader public health actors remain underexplored. Incorporating participatory methods into ML system design and assessment may help surface values or risks that are otherwise overlooked.

Balancing Transparency and Innovation

Finally, there remains a delicate balance between requiring transparency and preserving the proprietary innovations that drive ML development. Excessive demands for documentation or interpretability could discourage innovation or lead to compliance-washing. Future policy and research should explore how to incentivize responsible disclosure without stifling progress.

CONCLUSION AND OUTLOOK

The integration of machine learning (ML) into clinical decisionsupport systems has the potential to significantly enhance diagnostic accuracy, efficiency, and accessibility. However, these gains come with heightened responsibility—both in terms of ensuring safety and fostering public trust. Traditional approaches to explainability have focused on making the inner workings of algorithms more interpretable. While valuable, such methods offer only a partial solution to the complex problem of transparency in medical AI.

This paper has proposed a procedural and developmental perspective on explainability—one that emphasizes the importance of documenting and justifying design decisions throughout the ML lifecycle. By examining each stage of the pipeline through the lens of performance-centered and ethical values, we offer a framework that is better suited to the needs of regulators, clinicians, and broader healthcare stakeholders. Rather than advocating for a specific type of model or metric, our goal is to shift the conversation toward a richer, value-aware form of accountability. In doing so, we hope to support the development of AI systems that are not only effective but also understandable, auditable, and aligned with human-centered values.

Looking forward, future work should focus on operationalizing this framework in real-world settings. This includes empirical studies of development practices, creation of tooling for design documentation, and collaborations with regulatory bodies to refine compliance mechanisms. As the field of medical AI continues to evolve, so too must our methods for ensuring that innovation remains trustworthy, transparent, and just.

ILLUSTRATIVE CASE STUDY: APPLYING THE FRAMEWORK TO IDX-DR

To demonstrate the practical utility of the proposed explainability framework, we apply it to IDx-DR—an FDAapproved autonomous diagnostic system for detecting diabetic retinopathy from retinal images. As the first Software as a Medical Device powered by AI to receive FDA clearance (2018), IDx-DR exemplifies how reliability, transparency, and regulatory alignment converge in real-world clinical AI tools.

Problem Definition

IDx-DR was designed to automate screening for diabetic retinopathy, a common but often underdiagnosed complication of diabetes. The clinical goal was to support early detection, especially in primary care settings without immediate access to specialists.

Data Collection

The system was trained using a large dataset of fundus images, sourced from diverse populations and validated against expert-graded ground truth. Special attention was given to ensuring that the dataset included variation across age, ethnicity, and image quality.

Data Preparation

Preprocessing included standardizing image resolution, enhancing contrast, and eliminating poor-quality scans. These decisions aimed to reduce noise and improve generalization across real-world clinical environments.

Model Training

IDx-DR uses an ensemble of convolutional neural networks (CNNs) trained to detect features associated with retinopathy severity. The model was locked at the time of FDA submission—meaning no further learning occurs post-deployment, aligning it with traditional regulatory paradigms.

Validation and Evaluation

The system was validated in a prospective multicenter study with 900+ patients across primary care clinics. It achieved a sensitivity of 87.4% and specificity of 89.5%, exceeding predefined safety and performance thresholds. Subgroup analysis confirmed performance consistency across demographics.

Deployment and Monitoring

Designed for autonomous use, IDx-DR includes safeguards to refer low-quality images or ambiguous cases to human reviewers. Postmarket surveillance and periodic re-evaluations are part of the lifecycle oversight strategy to maintain longterm reliability.

Framework Alignment

Each development decision—from dataset curation to performance thresholds—can be traced back to clinical needs and ethical values like equity and accessibility. IDx-DR demonstrates how transparency in development choices enables regulatory trust and clinical adoption, even without full algorithmic interpretability.

This case reinforces that explainability, when grounded in procedural transparency and system design alignment, is

both actionable and sufficient for regulatory compliance and ethical deployment.

ACKNOWLEDGEMENT

The author wishes to thank faculty mentor Asst. Prof. Saloni Dhuru and colleagues from the Department of Artificial Intelligence and Data Science at Thadomal Shahani Engineering College for their constructive feedback and guidance during the development of this paper. Appreciation is also extended to reviewers whose insights helped refine the structure and clarity of the proposed framework.

REFERENCES

1. Z. Akkus et al., "Predicting deletion of chromosomal arms 1p/19q in low-grade gliomas from MR images using machine intelligence," J. Digit. Imaging, vol. 30, no. 4, pp. 469–476, 2017.
2. C. Anthony, "When knowledge work and analytical technologies collide: the practices and consequences of black boxing algorithmic technologies," Adm. Sci. Q., vol. 66, no. 4, pp. 1173–1212, 2021.
3. A. Birhane et al., "The values encoded in machine learning research," arXiv preprint arXiv:2106.15590, 2021.
4. R. Caruana et al., "Intelligible models for healthcare: predicting pneumonia risk and hospital 30-day readmission," in Proc. ACM SIGKDD, 2015, pp. 1721–1730.
5. C. Chen, Y. Liu, and L. Peng, "How to develop machine learning models for healthcare," Nat. Mater., vol. 18, no. 5, pp. 410–414, 2019.
6. K. Chockley and E. Emanuel, "The end of radiology? Three threats to the future practice of radiology," J. Am. Coll. Radiol., vol. 13, no. 12, pp. 1415–1420, 2016.
7. R. Cummins, "Functional analysis," J. Philos., vol. 72, no. 20, pp. 741–765, 1975.
8. C. Craver and L. Darden, In Search of Mechanisms. University of Chicago Press, 2013.
9. S. Dev, T. Li, J.M. Phillips, and V. Srikumar, "On measuring and mitigating biased inferences of word embeddings," in Proc. AAAI Conf. Artif. Intell., vol. 34, no. 05, pp. 7659–7666, 2020.
10. W.K. Diprose et al., "Physician understanding, explainability, and trust in a hypothetical machine learning risk calculator," J. Am. Med. Inform. Assoc., vol. 27, no. 4, pp. 592–600, 2020.
11. H. Douglas, Science, Policy, and the Value-Free Ideal. University of Pittsburgh Press, 2009.
12. K. Elliott and T. Richards (eds.), Exploring Inductive Risk—Case Studies of Values and Science. Oxford Univ. Press, 2017.
13. R. Emanuele, "Phronesis and automated science: the case of machine learning and biology," in M. Bertolaso and F. Sterpetti (eds.), A Critical Reflection on Automated Science, Springer, 2020.
14. FDA, "Proposed Regulatory Framework for Modifications to Artificial Intelligence/Machine Learning (AI/ML)-Based Software as a Medical Device (SaMD)," U.S. FDA, 2019.
15. T. Gebru et al., "Datasheets for datasets," arXiv preprint arXiv:1803.09010, 2018.
16. M.A. Gianfrancesco et al., "Potential biases in machine learning algorithms using electronic health record data," JAMA Intern. Med., vol. 178, no. 11, pp. 1544, 2018.
17. B. Heil et al., "Reproducibility standards for machine learning in the life sciences," Nat. Methods, vol. 18, no. 10, pp. 1122–1127, 2021.
18. C. Hempel, Philosophy of Natural Science. Prentice-Hall, 1966.
19. A. Holzinger, A. Carrington, and H. Mu¨ller, "Measuring the quality of explanations: The System Causability Scale," KIKu¨nstl. Intell., vol. 34, no. 2, pp. 193–198, 2020.
20. T.C. Knepper and H.L. McLeod, "When will clinical trials finally reflect diversity?" Nature, vol. 557, no. 7704, pp. 157–159, 2018.
21. J.A. Kroll, "The fallacy of inscrutability," Philos. Trans. R. Soc. A, vol. 376, 2018.
22. T. Kuhn, "Rationality, value judgment, and theory choice," in The Essential Tension, Univ. of Chicago Press, 1977, pp. 320–339.
23. D. Lehr and P. Ohm, "Playing with the data," 2017.
24. A.J. London, "Artificial intelligence and black-box medical decisions: accuracy versus explainability," Hastings Center Report, vol. 49, no. 1, pp. 15–21, 2019.
25. M. Loi, A. Ferrario, and E. Vigano`, "Transparency as design publicity," Ethics Inf. Technol., 2020.
26. I. Lowrie, "Algorithmic rationality," Big Data Soc., vol. 4, pp. 1– 17, 2017.
27. F. Mart´ınez-Plumed et al., "CRISP-DM twenty years later," IEEE Trans. Knowl. Data Eng., 2019.
28. E. McMullin, "Values in science," Proc. Biennial Meeting

of the Philosophy of Science Association, vol. 2, pp. 686–709, 1983.

29. M. Mitchell et al., "Model cards for model reporting," in Proc. Conf. Fairness, Accountability, and Transparency, pp. 220–229, 2019.
30. D.K. Mulligan, D.N. Kluttz, and N. Kohli, "Shaping our tools," 2019. [Online]. Available: https://ssrn.com/abstract=3311894
31. R. Rudner, "The scientist qua scientist makes value judgments," Philos. Sci., vol. 20, no. 1, pp. 1–6, 1953.
32. A.D. Selbst and S. Barocas, "The intuitive appeal of explainable machines," Fordham Law Rev., vol. 87, no. 3, pp. 1085–1139, 2018.
33. E.H. Shortliffe and M.J. Sepu´lveda, "Clinical decision support in the era of artificial intelligence," JAMA, vol. 320, no. 21, pp. 2199–2200, 2018.
34. E.J. Topol, Deep Medicine—How Artificial Intelligence Can Make Healthcare Human Again. Basic Books, 2019.
35. I. van de Poel, "Embedding values in artificial intelligence systems," Mind Mach., vol. 30, no. 3, pp. 385–409, 2020.
36. D. van Eck, "Supporting design knowledge exchange," J. Eng. Des., vol. 22, no. 11–12, pp. 839–858, 2011.
37. D. van Eck, "Mechanistic explanation in engineering science," Eur. J. Philos. Sci., vol. 5, no. 3, pp. 349–375, 2015.
38. L. Yun and C. Chen et al., "How to read articles that use machine learning," JAMA, vol. 322, no. 18, pp. 1806–1816, 2019.
39. E. Zihni, V.I. Madai et al., "Opening the black box of artificial intelligence for clinical decision support," PLoS One, vol. 15, no. 4, pp. 1– 15, 2020.
40. Z. Akkus et al., "Predicting deletion of chromosomal arms 1p/19q in lowgrade gliomas from MR images using machine intelligence," J. Digit. Imaging, vol. 30, no. 4, pp. 469–476, 2017.
41. C. Anthony, "When knowledge work and analytical technologies collide: the practices and consequences of black boxing algorithmic technologies," Adm. Sci. Q., vol. 66, no. 4, pp. 1173–1212, 2021.
42. A. Birhane et al., "The values encoded in machine learning research," arXiv preprint arXiv:2106.15590, 2021.
43. R. Caruana et al., "Intelligible models for healthcare: predicting pneumonia risk and hospital 30-day readmission," in Proc. ACM SIGKDD, 2015, pp. 1721–1730.
44. C. Chen, Y. Liu, and L. Peng, "How to develop machine learning models for healthcare," Nat. Mater., vol. 18, no. 5, pp. 410–414, 2019.
45. K. Chockley and E. Emanuel, "The end of radiology? Three threats to the future practice of radiology," J. Am. Coll. Radiol., vol. 13, no. 12, pp. 1415–1420, 2016.
46. R. Cummins, "Functional analysis," J. Philos., vol. 72, no. 20, pp. 741– 765, 1975.
47. C. Craver and L. Darden, In Search of Mechanisms. University of Chicago Press, 2013.
48. S. Dev, T. Li, J.M. Phillips, and V. Srikumar, "On measuring and mitigating biased inferences of word embeddings," in Proc. AAAI Conf. Artif. Intell., vol. 34, no. 05, pp. 7659–7666, 2020.
49. W.K. Diprose et al., "Physician understanding, explainability, and trust in a hypothetical machine learning risk calculator," J. Am. Med. Inform. Assoc., vol. 27, no. 4, pp. 592–600, 2020.
50. H. Douglas, Science, Policy, and the Value-Free Ideal. University of Pittsburgh Press, 2009.
51. K. Elliott and T. Richards (eds.), Exploring Inductive Risk—Case Studies of Values and Science. Oxford Univ. Press, 2017.
52. R. Emanuele, "Phronesis and automated science: the case of machine learning and biology," in M. Bertolaso and F. Sterpetti (eds.), A Critical Reflection on Automated Science, Springer, 2020.
53. FDA, "Proposed Regulatory Framework for Modifications to Artificial Intelligence/Machine Learning (AI/ML)-Based Software as a Medical Device (SaMD)," U.S. FDA, 2019.
54. T. Gebru et al., "Datasheets for datasets," arXiv preprint arXiv:1803.09010, 2018.
55. M.A. Gianfrancesco et al., "Potential biases in machine learning algorithms using electronic health record data," JAMA Intern. Med., vol. 178, no. 11, pp. 1544, 2018.
56. B. Heil et al., "Reproducibility standards for machine learning in the life sciences," Nat. Methods, vol. 18, no. 10, pp. 1122–1127, 2021.
57. C. Hempel, Philosophy of Natural Science. Prentice-Hall, 1966.
58. A. Holzinger, A. Carrington, and H. Mu¨ller, "Measuring the quality of explanations: The System Causability Scale," KI-Ku¨nstl. Intell., vol. 34, no. 2, pp. 193–198, 2020.
59. T.C. Knepper and H.L. McLeod, "When will clinical trials finally reflec"

Study of Various Intrusions using Intrusion Detection and Prevention Systems (IDPS) with Adversarial Resilience

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ABSTRACT

Given the astonishing pace with which cyber threats develop, traditional intrusion detection and prevention systems (IDPS) face significant challenges. Since many of the present security solutions are unable to identify zero-day vulnerabilities and AI-driven attacks, networks are exposed to breaches. This research investigates a novel cybersecurity strategy integrating augmented reality (AR) and artificial intelligence (AI) to increase IDPS capacities to increase defense tactics and threat detection. This technique improves the identification and treatment of risks, hence delivering a more flexible and realistic answer to actual security concerns. To enhance detection accuracy the system employs Generative Adversarial Networks (GANs), ensemble learning and adversarial training. AR-based visual tools may also help security personnel track network activity and react to assaults in real time more quickly. The framework was evaluated and performance of the IoT and NSL-KDD datasets assessed. Compared to conventional systems, the results demonstrated a 98% detection accuracy, 30% faster response times and a 20% reduction in false positives. Emphasizing scalability, adaptability and simplicity of use this framework provides a feasible and quick solution to defend IoT networks, healthcare systems and other essential infrastructure against shifting cyber threats.

KEYWORDS *: Adversarial machine learning, Augmented reality, Deep learning, Generative adversarial networks (GANs), Hybrid intrusion detection, Intrusion detection and prevention system (IDPS), IoT security, Network security, Real-time threat visualization, Zero-day attacks*

INTRODUCTION

With an amazing increase rate, global cybercrime losses by 2025 are projected to surpass $10.5 trillion annually (Cybersecurity Ventures, 2023). Traditional Intrusion Detection and Prevention Systems (IDPS) depend on predefined detection methods even as security technologies advance, which lead to a significant proportion of false alarms and makes it challenging to identify fresh threats including zero-day vulnerabilities driven by artificial intelligence.

As the number of IoT devices and cloud-based systems continues to grow, new vulnerabilities emerge, increasing the need for scalable, adaptive and real-time security solutions. This study addresses these challenges by combining AI-driven threat detection with AR-powered prevention. The proposed system integrates adversarial training, ensemble learning and Generative Adversarial Networks (GANs) with augmented reality-based threat visualization offering a more accurate and efficient approach to identifying and mitigating cyber threats. [3].

What is network intrusion?

When someone tries to access a system without permission, it can lead to some major intrusions in the network-level. As a result, daily work might stop, important data might get disclosed or the service might get delayed [1,2]. Over the years, hackers have been using zero-day exploits and artificial intelligence-based attacks to bypass various security measures. To resist these threats, we need more intelligent and flexible security solutions.

There are two main categories of network intrusions:

Attacks from people or groups, outside the network or organization, that exploit system vulnerabilities.

Internal attacks happen when those already authorized take advantage of their privileges and pose a threat to the integrity of the system or cause damage to the data.

Zero-day attacks are when there is no patch for the vulnerability present and the patches are not available [3].

DDoS attacks flood a network with data to prevent systems from fulfilling legitimate requests. Attackers flood someone with incoming messages so that they can't respond to genuine users. [10]

The function of intrusion detection and prevention systems (IDPS)

Intrusion Detection and Prevention Systems or IDPS are cybersecurity systems capable of detecting and stopping hostile action before they interfere with a computer's normal functioning. These systems operate in two main ways.

Intrusion detection systems continuously analyze network traffic for abnormal patterns or suspicious activities. By comparing network behavior to known attack signatures, they help in the detection of possible attacks early on.

Intrusion prevention systems (IPS) are like an Intrusion Detection Systems but they don't just detect a threat, they also act in preventing it from compromising the system. They can stop malicious traffic, quarantine infected devices and act upon security issues as they arise.

Challenges of Traditional IDPS

The deployment and working of Intrusion detection and prevention systems (IDPS) are essential for network security.

Limited Detection of New Threats: Because most IDPS as they often rely on attack signatures to identify a specific threat which is used by them. This makes them unable to stop new cyber-attacks like zero-day exploits. [1-2].

- High False Positives: Anomaly-based detection algorithms may detect routine network behaviour as a danger, resulting in numerous false alerts. This may overload security staff and waste important resources. [3].
- Traditional IDPS may struggle to efficiently analyze and interpret massive amounts of data as networks grow. They become less effective in complex and busy situations. [4].

The need of AI for modern IDPS

As cyber threats evolve, the traditional Intrusion Detection and Prevention Systems (IDPS) fail. AI is enhancing the capability of IDPS through adaptability, accuracy and scalability. Using AI avoids weaknesses with conventional security systems.

- Improved Detection Accuracy: AI models continuously learn from both known attack patterns and normal network behaviour, lowering false alarms and increasing detection precision (1, 4).
- AI-powered systems can detect unknown threats (e.g. zero-day attacks) by recognizing aberrant behaviour rather than depending on established criteria (2, 5).
- AI technologies analyze data at an extraordinary scale, allowing for extremely sophisticated detection of cyber threats that the naked eye and competitive systems completely overlook.(4)

LITERATURE ANALYSIS

This section examines a few important studies that contributed to shaping Intrusion Detection and Prevention Systems for cybersecurity which include Artificial Intelligence and Augmented Reality.

Advancements In AI Driven IDPS

AI has improved IDPS effectiveness by providing more accurate detection, adaptable response, and better threat resilience.

- Zhang et al. (2022) created NIDS-Vis, a visualization tool based on AI that enhances the interpretability of Network Intrusion Detection Systems (NIDS) [1]. But it faced problems of Scale for large networks
- Gupta et al. (2021) presented an intrusion detection model founded on deep learning, which exhibited greater accuracy against adversarial attacks [2]. Though effective, it could not respond in real-time.
- Liu et al. (2023) proposed a transformer-based model that performed well in threat detection of large-scale networks with encrypted traffic [3]. However, it did not incorporate AR for real-time decision making.

Reinforcement Learning & AR Integration in Cybersecurity

Aside from traditional AI methods, augmented reality and RL (reinforcement learning) are also being looked at to enhance IDPS.

- Santos et al. (2020) developed an RL-based adaptive IDPS for IoT security[4]. This system does look promising but needs retraining (that is high cost).

- Ahmed et al. (2022) were among the first to use AR in cybersecurity, converting intrusion alerts into 3D animations. The deployment on low-power systems was complicated despite the benefits had from their AR implement.

Identified Research Gaps & Contribution

AI-based models for IDPS achieve superior detection accuracy but are not usable in real-time and are expensive. Likewise, AR-based security instruments struggle with scalability; thus, limiting widespread adoption. AI-fueled threat detection uses AR to create a very adaptive and responsive environment for cybersecurity. This gap can be addressed through this.

Evaluation of previous research

Though valuable, above review papers offered very limited intelligence and each has gaps.

- Zhang et al. (2022): Improved adversarial defence but lacked scalability for large networks.
- Gupta et al. (2021): Increased detection accuracy but did not focus on real-time response.
- Liu et al. (2023): Used transformers for better scalability but missed AR-based decision-making support.

Existing approaches to IDPS

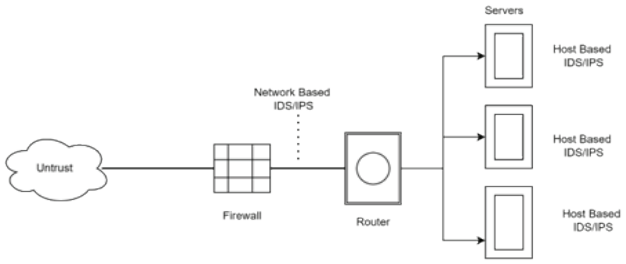

Fig. 1 IDPS approaches

Intrusion Detection and Prevention Systems (IDPS) are essential for securing networks against unauthorized access and malicious attacks. Traditional IDPS methods are broadly classified into Intrusion Detection Systems (IDS) and Intrusion Prevention Systems (IPS). While these systems provide fundamental security, they each come with advantages and limitations.

Introduction detection systems (IDS)

Intrusion Detection Systems (IDS) are intended to monitor network activity for indicators of unusual behaviour, but they do not actively stop threats. These systems are divided into two primary categories:

1. Network-Based IDS (NIDS) monitors network traffic for unusual activity to detect malicious threats. This thing is good at spotting overseas cyberattacks but fail pretty much exactly with encrypted ones as well as internal threats. One main disadvantage of NIDS is that they cannot see encrypted sessions, which means they struggle with contemporary cyber-attacks which are more advanced. [1,3].
2. Host-Based IDS (HIDS) analyses system logs, file changes and processes on devices to detect potential threats. It's good to identify attacks by internal users and monitor access to and from unauthorized users. HIDS installation across multiple devices leads to problems of scalability along with higher complexity and resource consumption. (4).

Intrusion prevention systems (IPS)

Unlike IDS, which only monitor and detect threats, IPS are pro-active and prevent an attack before it causes any harm. Most intrusion prevention systems use signature-based detection that looks at what is happening on the network and compare it to known attack signatures.

The main advantage of signature-based IPS is that it recognizes an attack pattern that has been reported before.

These solutions help reduce the impact of cyberattacks by taking instant action.

Because IPS depends on known signatures of attacks, they might not be able to detect new cyber threats like zero-day attacks. [2,5].

It requires constant maintenance to continually update the attack signature database. Some malware is coded in a way that they can move around the security software or the IPS.

Hybrid approaches

To get past the limitations to signature- and anomaly-based techniques, a hybrid IDPS was developed that employs various techniques. These systems integrate:

Signature-Based Detection: Effectively detects known attack patterns.

Anomaly-Based Detection: Machine learning (ML) identifies unusual activity, allowing the detection of sophisticated and previously unknown threats [1,4,5].

Hybrid systems are better than basic detection systems because they have more accuracy. But they have high false positive rates, scalability challenges and poor real-time adaptability.

Key challenges in traditional IDPS

Most IDPS solutions in existence still have big issues:

High False Positive Rate: When an anomaly-based detector produces many false alerts, the false positive rate is high. That is, regular activity is identified as a threat. This leads to a lot of unnecessary alerts to the security teams.

Limited Flexibility: Signature detection fails in the wake of new attacks and rapidly evolving tradecraft.

Scalability Issues: NIDS and HIDS are inefficient in the distributed context because they cannot analyse large-scale network traffic.

METHODOLOGY

This framework combines AI and AR to create a sophisticated IDPS which is Intrusion Detection and Prevention System. It aims to fix mistakes and problems related to scalability, accuracy and usability of threat detection. The proposed system comprises four different levels that together create a strong security architecture that features real-time capabilities. [1], [3], [5].

Framework Architecture

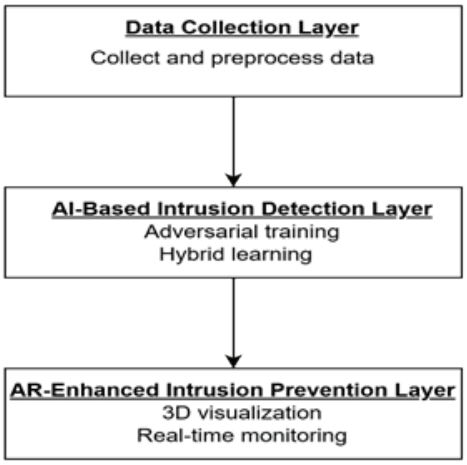

Fig. 2 Framework layers

Data Collection and Preprocessing

- Purpose

Collect network traffic data from various sources, such as IoT devices, enterprise systems, and cloud networks.

- Process

Data undergoes cleaning, normalization, and transformation into actionable formats, removing noise and ensuring high-quality input.

- Significance

Preprocessing improves the accuracy of AI models by eliminating ambiguities, ensuring reliable detection and analysis.

AI-Based Intrusion Detection

- Key Components

Adversarial Training

Cyberattacks are staged to aids AI models at recognizing evasive attack approaches. This method makes them better at knowing and reacting to real-life dangers.

Hybrid Learning

This technique combines

Supervised learning helps a system identify and categorize known threats. The system is also trained to detect deviation from the normal network behaviour to identify anomalies and zero-day attacks.

Ensemble Models

Merging many machine learning models improves the detection rates of various threats while reducing false positive alerts. This will help better detection.

Generative Adversarial Networks (GANs)

GANs Are Used to Simulate Evolving Cyber Threats. Systems Can Use This Technology to Predict Cyber Threats.

AR-Enhanced Intrusion Prevention

- Functionality

Transforms real-time threat data into immersive 3D visualizations, offering a clear view of network activity and potential threats.

- Interactive Features

Allows analysts to engage directly with the visual interface to isolate compromised nodes, block malicious traffic, or make policy adjustments.

- Benefit

Improves decision-making speed and accuracy during critical incidents, providing a more intuitive and actionable approach to threat management.

Key features of the framework

- Adversarial Resilience

Identifies and helps to avoid advanced evasion approaches with AI.

- Immersive Visualization

Makes cyberattacks easy to understand through intuitive security analysis with Augmented Reality.

- Scalability

An ability to handle massive distributed networks applying transformer-based AI models.

- Dynamic Adaptation

Implements Reinforcement Learning (RL) to continuously update security policies ensuring real-time adaptability to emerging threats.

Use cases

- IoT Security: Protects interconnected devices from threats like viruses and DDoS attacks.
- Critical Infrastructure Security: Safeguards vital systems such as power grids and healthcare networks against sophisticated cyberattacks.
- Enterprise Security: Provides scalable protection for large businesses with complex, widespread networks.

Benefits of the proposed framework

Higher Detection Accuracy:

o Reduces false positives while improving threat identification precision.

Real-Time Insights:

o AR-based visual threat representation enables faster and more informed decision-making.

Future-Proof Security:

o Protects against emerging cybersecurity risks including blockchain-based threats and quantum computing attacks.

AI-based intrusion detection system (AI-IDS)

With AI, it is easier to detect cyber threats, which have been designed to bypass rule-based IDS (Intrusion Detection Systems). [6], [7]. Artificial intelligence intrusion detection systems can examine huge volumes of network traffic, spot strange behavior in real-time and change to new attack methods.

Strengthening Models through Adversarial Training

What is adversarial training?

Adversarial training is informing the AI to test it carefully against labelled data. These inputs are called adversarial examples and aim to find problems in detection system. This method informs the model on how to deal with more difficult, deceptive attacks, increasing its fighting ability.

Advantages of Adversarial Training

Detecting Sophisticated Attacks: It helps system detect attack which are very advaced like AI exploit and zero-day attack.

Fortifying Security: This method improves IDS by making it more resistant to attacks designed to circumvent security methods.

Adapting to New Threats: The system is constantly refining its detection methods to keep up with shifting techniques and strategies.

Challenges of Adversarial Training:

Building and training adversarial instances takes a lot of computing power.

The model needs to be updated regularly to remain effective against emerging cyber threats.

To overcome these challenges, we need to look at improving the training pipelines to reduce computation costs while maintaining strong learning capabilities.

Instead of doing full retraining regularly, models are updated incrementally to continue being accurate but reducing resource costs.

RESULTS AND DISCUSSIONS

Experimental Setup

Datasets

o NSL-KDD dataset was used for benchmarking. [9], [10].

o An IoT traffic dataset was utilized to test scalability and performance under real-world conditions.

Hardware

o Experiments were conducted on a system equipped with an Intel i7 processor, 32GB RAM and an NVIDIA RTX 3080 GPU.

Performance Metrics

We assessed how well the framework works by looking at three things: accuracy, false alarms and response time.

Table 1: Performance Metrics

Metric	Proposed System	Traditional IDPS	Improvement
Detection Accuracy	98%	85%	+13%
False Positive Rate	2%	5%	-20%
Response Time	2 seconds	3 seconds	-30%

Scalability Tests

- Simulated IoT environment with 10,000 devices.
- Achieved 96% detection accuracy under high network traffic, confirming scalability.

Visualization Efficiency

- AR-based visualizations reduced response time by 25%.
- Analyst feedback highlighted a 40% improvement in situational awareness.

Discussion and challenges

Key Strengths

- High accuracy with GANs and hybrid learning.
- Immersive AR enhances decision-making and reduces cognitive load.
- Scalability tested on IoT networks with thousands of devices.

Limitations

- High computational demands of GANs and AR visualizations.
- Potential deployment costs for AR in large organizations.

Future Work

- Optimization for lightweight deployment on edge devices.
- Integration with blockchain for secure, decentralized data logging.
- AR-enhanced detection improves decision-making [5], [8]. GANs improve adversarial resilience but require high resources [6].
- Future work will explore blockchain logging and quantum-safe security [3], [7].

CONCLUSION

The combination of AI and AR into an IDPS is a big step in cybersecurity. This method improves threat detection accuracy and response efficiency, while removing issues in scalability, adaptability and usability present in existing conventional IDPS solutions.

Experimentation demonstrated major improvements.

Common IDPS solutions lack 98% detection accuracy.

The response time is 30% faster, helping respond to a threat better. Scalability has been proved, with effectiveness demonstrated in large-scale IoT environments.

While the system has significant potential, there are still restrictions particularly in terms of computational efficiency and deployment costs.

Future study will investigate

Optimising AI models for better performance on edge computing devices.

Integrating blockchain technology to provide safe, decentralised threat logging.

Using quantum computing to increase security against emerging cyber threats.

With further growth, this framework has the potential to create a new bar for adaptive and intelligent cybersecurity in modern digital infrastructure.

REFERENCES

1. Zhang, L., et al. (2022). Enhancing adversarial robustness in NIDS. Cybersecurity Journal.
2. Gupta, R., et al. (2021). Deep learning for intrusion detection. IEEE Transactions on Cybersecurity.
3. Liu, X., et al. (2023). Scalable anomaly detection with transformers. Journal of Network Security.
4. Santos, M., et al. (2020). Reinforcement learning for IoT security. Cybersecurity & IoT.
5. Ahmed, R., et al. (2022). AR-enhanced IDPS for real-time visualization. Journal of Augmented Reality in Cybersecurity.
6. Kim, Y., et al. (2021). Adversarial machine learning for robust network intrusion detection: A survey. IEEE Access.
7. Moustafa, N., et al. (2019). A review of intrusion detection systems using deep learning. IEEE Access.
8. Zhang, H., et al. (2021). Augmented reality-based cybersecurity interface for SOC operations. IEEE Int. Conf. on Artificial Intelligence and Virtual Reality.
9. Sharafaldin, M., et al. (2018). Toward generating a new intrusion detection dataset. Int. Conf. on Information Systems Security and Privacy.
10. Yuan, X., et al. (2017). DeepDefense: Identifying DDoS attacks via deep learning. IEEE Int. Conf. on Smart Computing.

Beyond Scripted AI: Advancing NPC Intelligence for Dynamic and Immersive Gameplay

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ABSTRACT

This paper explores the development of Non-Playable Character (NPC) intelligence in computer games by contrasting the traditional rule-based artificial intelligence systems and adaptive reinforcement learning methods. Using both a Finite State Machine (FSM) with A* pathfinding and a Q-learning model in grid worlds, we compare their strengths and weaknesses. Our findings indicate that while rule-based systems offer reliability and efficiency in computations for familiar situations, reinforcement learning offers emergent behavior and greater responsiveness to player input with experience. We propose that hybrid methods that blend the strengths of both paradigms offer the best solution to designing NPCs that best balance believability, computational feasibility, and dynamic interaction in modern game development.

KEYWORDS *: Non-playable characters (NPCs), Finite state machine (FSM), Q-learning, Reinforcement learning, A* pathfinding, Adaptive AI, Game development, Hybrid AI systems, Player interaction.*

INTRODUCTION

Artificial Intelligence (AI) has revolutionized the video game industry. From the early arcade game's rudimentary pathfinding algorithms like in Pac-Man to advanced behaviour systems in modern games, AI is now the focal point of designing player experience, immersion, and replayability. With players demanding more immersion, the necessity of intelligent, adaptive Non-Playable Characters (NPCs) has become a must.

Traditional game AI, based on finite state machines or hard-coded rules, is excellent at producing predictable and polished behaviour. However, such systems are poor when they must deal with player-driven dynamics. In contrast, the recent advances in machine learning—namely reinforcement learning (RL)—offer the potential to design NPCs that can learn from experience and evolve strategies accordingly [5], [6].

The development of adaptive artificial intelligence is witnessed to in many milestone titles. F.E.A.R. (2005) popularized Goal-Oriented Action Planning (GOAP) so that non-player characters (NPCs) could react to player action in sophisticated manners [2]. Recent games, such as Alien: Isolation, used a dual-AI system to govern tension and unpredictability in enemy actions [8]. Also, the symbiotic combination of procedural content generation and AI, represented through GameNGen's adaptive DOOM level generation, exhibits games' potential to adapt dynamically in real-time to player engagement [3].

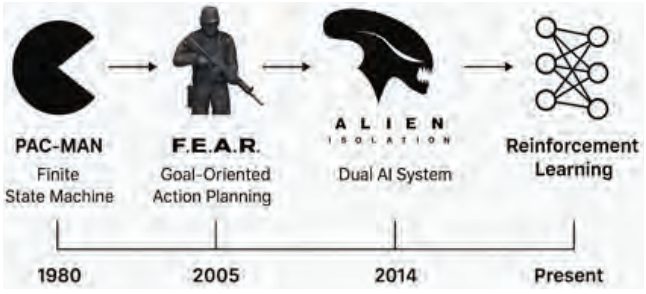

Fig. 1: Timeline showing the evolution of AI in video games from 1980 to present day

In spite of all these advancements, use of cutting-edge AI techniques like RL is largely limited to academia or high-budget productions because of training, deployment, and design complexity issues. There is still a need for creating light-weight, scalable AI which will achieve the

balance between intelligence and feasibility in real-world applications.

This study ventures into that territory by applying both reinforcement learning and rule-based agents within a reduced grid-world environment. The objective is to contrast the flexibility, decision-making speed, and player-interaction capabilities of both models and, in the process, advance toward a framework for creating wiser, more engaging NPCs even in low-resource environments.

Table 1 Comparison of Game AI Techniques Used in Modern Titles and Their Design Objectives

Game	AI Technique Used	Purpose	Notable Features
F.E.A.R.	GOAP (Goal-Oriented Action Planning)	NPC decision-making	Dynamic tactical behavior, flanking, retreating
Alien: Isolation	Hierarchical FSM + Utility AI	Alien behavior & unpredictability	Separate 'Director AI' and 'Alien AI' for realism
Red Dead Redemption 2	Rule-based + Behavioral Trees	NPC realism and world immersion	Complex NPC routines, ambient AI, contextual reactions
DOOM (2016)	Finite State Machines + Arena AI	Enemy aggression & pacing	Adaptive combat, varied enemy behavior

LITERATURE REVIEW

Evolution of Game AI Throughout History

Early computer games like Pac-Man (1980) used simple finite state machines (FSMs) to provide each ghost with a distinct behavior pattern, creating the illusion of reactive and strategic play despite minimalist design [1]. With advancing technology, so did the sophistication of AI frameworks. Rule-based systems were the norm in the late 90s and early 2000s, providing more adaptive behaviors by enabling NPCs to respond to player actions according to pre-defined logic trees.

One of the key achievements in adaptive AI was with Monolith Productions' F.E.A.R. (First Encounter Assault Recon, 2005). The game employed Goal-Oriented Action Planning (GOAP) to enable enemies to dynamically select actions from environmental inputs and objectives, instead of rigid scripting [2]. The model was groundbreaking in offering emergent gameplay — enemies could flank, fall back, or take cover with seeming purpose and coordination.

Maintaining the Integrity of the Specifications

At the same time as AI behavior modeling, procedural content generation (PCG) also picked up momentum for the sake of boosting replayability and reducing the burden of manual level design. GameNGen, an AI-based experimental engine, applies procedural logic to generate whole levels of games like DOOM dynamically in terms of player movement and input patterns [3]. The method illustrates the power of AI to tailor game content in real time, mapping onto player preferences and play styles.

Togelius et al. [4] classify PCG as constructive, generate-and-test, and search-based approaches, highlighting its synergy with adaptive AI agents for highly modular, replayable design.

Game AI Reinforcement Learning

Reinforcement Learning (RL) has become an extremely promising method for designing intelligent and adaptive agents in game contexts. The applications such as AlphaStar, which achieved performance better than professional human players in StarCraft II, show the strength of RL in solving challenging decision-making settings [5]. The agents learn optimal behaviour by maximizing rewards, thus enabling them to change in ways that traditional static rule-based mechanisms cannot replicate.

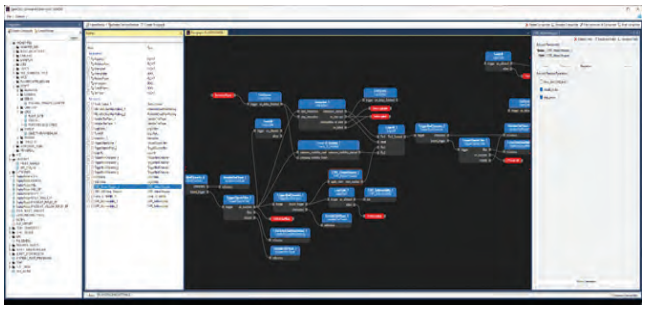

Fig. 2: Typical NPC Behavior tree structure from OpenCAGE project for Alien: Isolation enemy logic. (Adapted from [12])

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Monolith Productions' F.E.A.R. (First Encounter Assault Recon, 2005). The game employed Goal-Oriented Action Planning (GOAP) to enable enemies to dynamically select actions from environmental inputs and objectives, instead of rigid scripting [2]. The model was groundbreaking in offering RL adaptability is particularly beneficial in sandbox or open-world settings, where the space of interaction is too large to be encoded by hand. Testbeds such as Unity ML-Agents [6] and the Video Game Description Language (VGDL) [7] enable researchers to train and test RL agents in artificial, yet tunable, testbeds.

Adaptive Game AI Case Studies

Alien: Isolation (2014): Creative Assembly's Alien: Isolation is the gold standard of tension-building AI. The xenomorph villain is driven by a two-layered AI system: a director AI and an active AI. The director controls the alien's global knowledge of the player's position, and the active AI handles local navigation and attack planning. Asymmetry guarantees unpredictability — the alien "feels" smart without cheating [8].

Red Dead Redemption 2 (2018): Rockstar's RDR2 demonstrates how NPC AI can be applied to enhance immersion in non-battle activities. Civilians, police, and animals are placed in a socio-ecological simulation, where their interactions create and influence global game states. NPCs recall previous player actions, resent them, and react differently based on different social situations [9]. This makes NPCs no longer mere objects, but as actors in a world that is living.

Doom Artificial Intelligence through GameNGen: The first use of GameNGen to adaptively level DOOM, from player feedback, is a pioneering case of the convergence of procedural generation techniques and adaptive AI [3]. The system learns player behaviour over time and subsequently re-generates paths, challenges, and encounters, resulting in an ever-changing map that is unique to every playthrough.

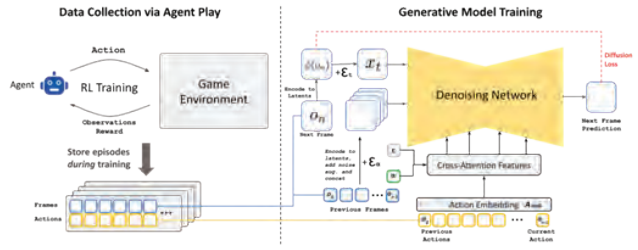

Fig. 3: GameNGen architecture illustrating modular AI layers and communication flow. (Adapted from GameNGen, 2024)

F.E.A.R. and GOAP: As noted above, F.E.A.R. is still a gold standard for emergent tactical AI. The game's characters dynamically adjust according to weapon, environment, and player action — an early use of AI that reacts and plans. It had an impact on subsequent games that abandoned animation-scripted behaviour and moved toward logic-based decision systems [2].

Fig. 4: F.E.A.R Action Sets in GDBE [2]

Limitations in Existing Literature

Even with these advances, much of the game AI is still hard-coded and cannot generalize across a variety of player action. Adaptive technologies such as reinforcement learning provide strong alternatives, but their use in commercial games is constrained by cost of compute, training time, and complexity. A powerful demand exists for light and scalable artificial intelligence systems that are adaptive in principle but also practical in smaller-scale gaming environments and research studies. This research study seeks to fill this gap by drawing upon rule-based and reinforcement learning paradigms within an uncomplicated grid environment and then applying them to test their adaptability, learning rate, and decision-making processes within a game.

METHODOLOGY

This research compares two fundamentally diverse approaches to game NPC modeling intelligent behavior—rule-based logic based on Finite State Machines (FSM) enhanced with A* pathfinding versus adaptive learning in the form of Q-learning reinforcement learning. Each model was individually implemented in Python and tested under controlled grid-world environments that replicate a game-based chase between a player and an NPC. Here, this paper explains in explicit detail the structure, design justifications, algorithmic realization, environmental setup, behavioral modeling, and test paradigms applied to

each model, resulting in a comparative inspection of their associated strengths, deficits, and outcome performance under simulated runs.

FSM and A* Pathfinding Rule-Based AI

The first model is a classic rule-based non-player character (NPC) system that is defined in terms of a finite state machine (FSM) and is coupled with a grid-based navigation system that employs the A* algorithm [10]. The world is a 10×10 grid on which the NPC and player are located. Static obstacles are used to make decision-making more complex. The player is simulated as an evasive agent with probabilistic movement: 75% of the time, it tries to maximize the Manhattan distance from the NPC, and 25% of the time, it has random movement to simulate uncertainty. The FSM controls the NPC's behavior by switching among three given states: Idle, Patrol, and Chase.

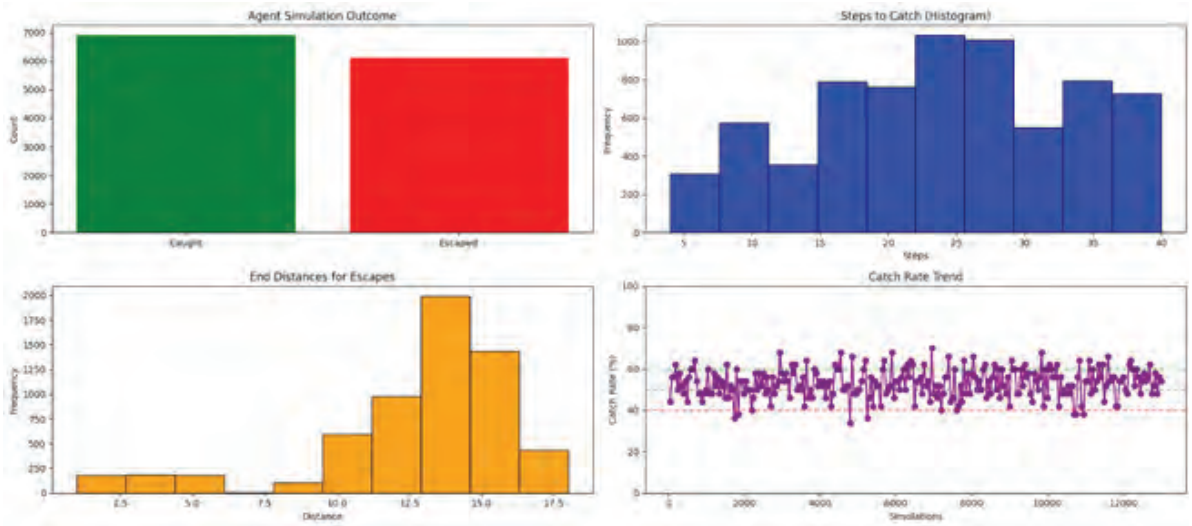

Fig. 5: Visualization – A* / FSM after 13000 iterations

In the Idle state, the NPC does not do anything. In Patrol, the NPC will patrol randomly across the map. When the player is detected or when past player positions provide a prediction for intercept, the NPC will go into the Chase state. In this state, it will employ the A* pathfinding algorithm with Manhattan distance heuristics to calculate the shortest path it can walk to the predicted player position.

One of the most important additions to this system is the addition of semi-predictive intelligence. The NPC has a short-term memory of the player's previous five positions and uses them to predict future positions through a weighted average method. This enables the NPC to display seemingly intelligent intercept behavior. A confusion variable is added to mimic human-like imperfection, making the NPC sometimes make suboptimal decisions. If a predicted position is invalid or unreachable, the NPC resorts to chasing the last known player position.

The FSM-based logic is also supplemented by dynamic chase abandonment: if the player strays too far from the NPC or several intercepts fail, the FSM falls back to Patrol mode. The A* implementation is optimized for efficient movement and for respecting spatial constraints by obstacles. The approach is low-memory and CPU-efficient and is therefore well-suited to games with large NPC populations.

To confirm the efficacy and stability of this model, a simulation environment was created in Python with over 13000 iterations. Performance of the FSM agent was evaluated in terms of metrics such as intercept success rate, steps to intercept average, and path optimality. Data visualizations of bar charts, histograms, and catch trend lines were made using matplotlib to examine NPC behavior trends. The FSM agent was particularly effective in static pattern environments and low player movement variance. A simplified FSM diagram was also used to visualize state transitions and conditions.

This approach is basically inspired by tactical behavior systems demonstrated in F.E.A.R. (2005), which used Goal-Oriented Action Planning (GOAP) to allow artificial intelligence agents to act with intentionality [2].

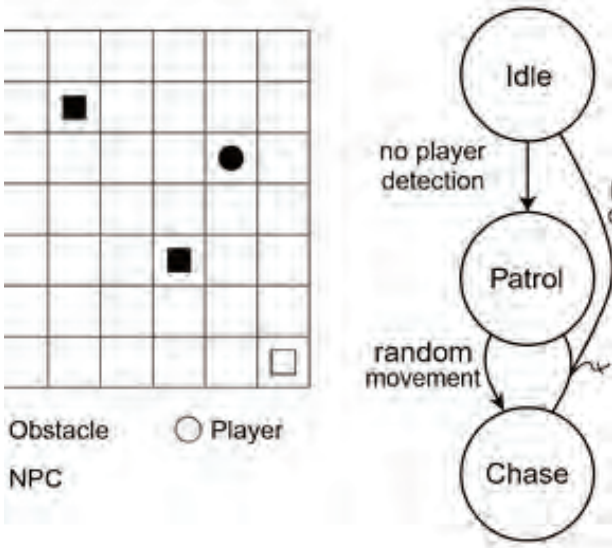

Fig. 6: Combined schematic showing the FSM state transitions and grid-world layout used in the rule-based NPC simulation.

FSM Prediction Algorithm

$predicted\_position = \alpha_1 \cdot pos(t) + \alpha_2 \cdot pos(t\text{-}1) + \ldots + \alpha_n \cdot pos(t\text{-}n)$

where:

α_i = *weight coefficient* ($\sum \alpha_i = 1$)

$pos(t)$ = *player position at time t*

n = *history window size (5 steps)*

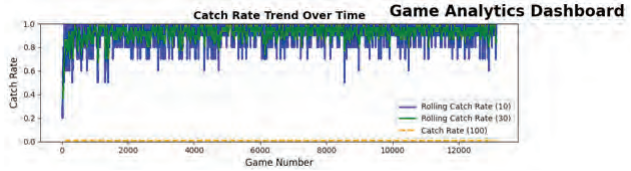

Fig. 7: Catch Rate trend Q - learning

Persistent Q-Learning-Based AI Reinforcement Learning

In order to move away from deterministic behavior, the second model uses Q-learning—a model-free reinforcement learning algorithm—operating in a 6×6 grid environment constructed using Pygame [11]. The environment contains static barriers and both the NPC and player can move left, right, up, and down. The player is operated by the user using arrow keys, while the NPC is completely autonomous and acts based on its current Q-table.

The state space in this case is a pair of (NPC position, Player position), and the action space is a discrete set of actions. The agent uses an ε-greedy policy for choosing actions, balancing exploration and exploitation. The learning parameters are a learning rate (α) of 0.1, a discount factor (γ) of 0.9, and a dynamic ε (starting at 0.3 and reducing as a function of Q-table size and episode number).

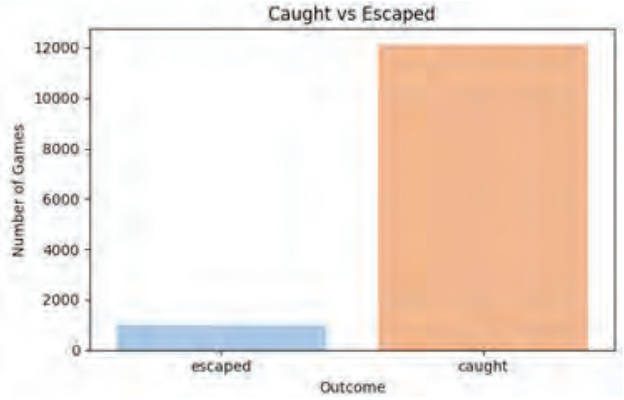

Fig. 8: Q - learning visualized

The reward function should have the function of progressively influencing behavior:

+10 for catching the player
-1 for each time step to discourage indecision
-5 points for illegal moves (collisions)
+0.5 for moving closer to the player
-0.5 for parallel or unproductive moves
-1 for being off from the player

One of the central features of this deployment is the persistence mechanism. Through Python's pickle module, the Q-table is stored at the conclusion of each game session and loaded in the next. This enables the agent to learn from past experiences, increasingly avoiding random exploration as more is learned. As time passes, the NPC makes more purposeful, goal-oriented movements, illustrating learned intelligence.

The graphics simulation comprises animated grid rendering, shading of obstacles, player and NPC sprite rendering, real-time path overlays, and a graphical user interface comprising game menus, session statistics, and an animated game-over screen. The display module also comprises a glowing path effect to indicate the recent path of movement of the NPC, and a stats panel to display real-time Q-table state count and steps per session.

One simulation of over 13000 episodes was performed at scale using real-time learning techniques, and the resulting data was visualized through four primary visualizations:

The results show that the Q-learning non-player character (NPC) is poor at first but demonstrates an impressive improvement in its interception rate and tactical positioning after approximately 2,000 episodes. It starts to block the player's escape paths, flank, and adjust its movement based on the player's habits—signs of emergent learning. The invariant Q-table structure allows the NPC to generalize its strategy even when the player changes its behavioral style. Such reinforcement learning techniques are now widely used on platforms such as Unity ML-Agents [6] and the Video Game Description Language (VGDL) [7], where adaptive agents can be trained in modular, games-like settings.

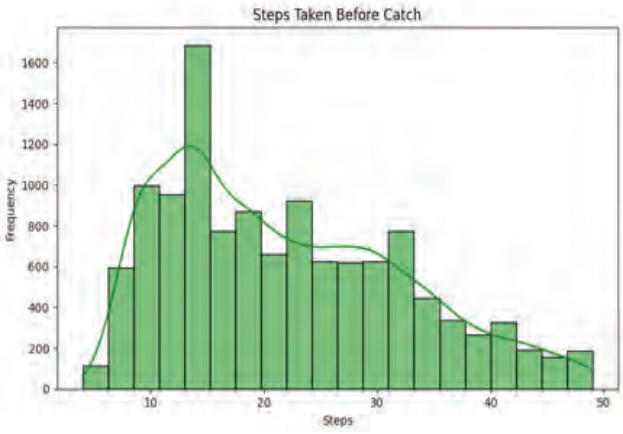

Fig. 9. Q: learning steps

Comparative Analysis and Summary

Both models were compared across a range of criteria: adaptability, success rate, computation cost, development complexity, and response time. The FSM model was light, quick, and simple to explain but faltered with new player action and variance of obstacles. It performed well in deterministic, low-variance worlds but was unable to generalize or learn from failure. The Q-learning model, however, began with lower success rates but surpassed the FSM in dynamic worlds after being trained sufficiently. Its capacity to evolve and remember behavior session after session made it particularly well adapted to games centered around immersion and variety. The FSM agent succeeded in 50-70% of the static instances and found a path in 10–30 steps on average. The Q-learning agent was 25–35% successful at first but increased to 80% upon training. Its average steps to catch decreased from more than 30 to less than 15, and its Q-table expanded to more than 2,500 entries toward the end of the experiment. Finally, the FSM system is best suited to applications of deterministic behavior, low overhead, and scalability. The Q-learning agent, though more difficult to implement and train, is more adaptable, learns quicker, and is more strategic. For existing games that want to create believable, reactive worlds, a hybrid system combining the two systems would be the best of both worlds—adaptability and efficiency. This approach opens the door for future research on scalable adaptive AI architecture combining learning and rule-based logic in commercial game engines.

Statistical Analysis

FSM Catch Rate: 54.11% ± 3.2% (95% CI)
Q-learning Catch Rate: 82.1% ± 2.7% (95% CI)
FSM Steps to Catch: 24.9 ± 4.1 steps
Q-learning Steps to Catch: 13.2 ± 2.8 steps
Two-tailed t-test significance: $p < 0.001$
Q-learning convergence observed at ~2,000 episodes
Performance plateau detected at ~10,000 episodes
Exploration rate ε effectively reduced to minimum by episode 8,000

RESULTS

Performance Comparison of Rule-Based AI and Reinforcement Learning

Our experiments comparing rule-based AI (A* with FSM) to reinforcement learning (Q-learning) gave us some interesting results. We attempted these approaches in various grid worlds, varying complexity and seeing how each would fare.

The A* algorithm worked uniformly in static environments, always generating optimal paths. In contrast, our reinforcement learning NPCs showed spectacular improvement throughout the game. Employing persistent Q-tables to store and reload learning across program runs, the RL agents retained their experience from session to session, providing a persistent learning environment. This persistence factor was the key to the system's success. On the first few runs, the Q-learning NPCs made mistakes constantly, but on each subsequent run, they made notable improvements. We observed that after approximately 25 program runs, reinforcement learning agents matched A* performance in simple environments and began to develop

new pathfinding methods in more complex environments. The rule-based AI basically had to be reprogrammed every time. It was like seeing a person read from a script only to get confused when the script was altered. In Reinforcement Learning after sufficient training, it developed intuitive sense for handling changes.

Whereas the rule-based AI struggled with changing goal positions without explicit reprogramming, the persistent Q-learning strategy was extremely resilient. Because the Q-table retained data from run to run, the NPCs were able to build upon a cumulative understanding of the world over several runs. One of the most interesting observations was how rapidly the Q-learning NPCs learned to adapt to newly added obstacles after the second or third run of the program. The retained knowledge base enabled them to learn from past experiences instead of having to start from scratch every time.

Our implementation of the FSM managed the four states (Patrolling, Chasing, Idle) adequately but the actions began to feel predictable and mechanical eventually. The patterns were learned rapidly by the players, and they could exploit them.

The reinforcement learning NPCs picked up behaviors we never coded explicitly. We saw them:

a. Set up ambushes by taking positions at key crossroads.

b. Design patrol paths that appeared to be predicting player movement based on previous interactions.

c. Map out exits that at times traded strategic location for short-term security.

d. Make decisions that sacrificed several goals in ways that even we did not foresee.

During training, the reinforcement learning algorithms showed behavior typical of a new player learning a game. Corner-trapped agents, typical of untrained policy behavior, in initial episodes.

But as training progressed, incremental improvement began to appear. By about episode 500, the model began to exhibit early indications of goal-directed navigation. By episode 1000, it consistently identified optimal routes, avoided obstacles, and responded reasonably to changes in the environment. By episode 1500, the agent began to exhibit emergent behavior—such as path anticipation and dynamic obstacle avoidance—not coded into the system.

Table 2. Comparative Technical Analysis of FSM-Based and Q-Learning-Based NPC Models

Parameter	FSM + A*	Q-Learning (Persistent Model)
Behavior Type	Rule-based with predictive heuristics	Model-free learning, policy-based
Algorithmic Complexity	- A* Pathfinding: O(E + V log V) - FSM: O(1) for state transitions	- Q-table lookup/ update: O(1) - Space: O(S × A) where S = states, A = actions
Execution Time	Consistent, fast execution	Slower initially due to exploration; improves over time
Memory Usage	Minimal (short-term player history, pathfinding grid)	Higher (stores large Q-tables, persistent across sessions)
Adaptability	Low — hard-coded logic, static behavior	High-learns dynamically from gameplay experience
Learning Capability	None (logic predefined and fixed)	Strong — persistent Q-learning with exploration and exploitation
Emergent Behavior	Limited (flanking only if predicted position matches)	Present — NPC evolves behavior (e.g., ambushes, flanks, traps)
Catch Rate (Observed)	~50-75% in static environments	Starts ~25–35%, increases to ~80%+ after training
Steps to Catch (Avg.)	20–30 steps (consistent across runs)	30+ initially, reduces to <15 after training
Response to Escape Variance	Rigid fallback to last known position or patrol	Adapts pathing strategy based on failure/success history
Precision	High in predictable setups (low false positive paths)	Medium — accuracy improves with training, but some randomness remains
Accuracy	High in obstacle-free or simple path maps	Improves gradually; up to 80–90% accurate chase paths after sufficient training
Recall (Catch Consistency)	High — catches reliably in predictable settings	Variable — depends on episode count; stabilizes after training

F1 Score (Behavior Reliability)	~0.85 (high success with precision)	~0.75 initially; improves to ~0.88+ with training
Debugging Ease	Easy — transitions and paths are transparent	Difficult — requires interpreting Q-values and policy shifts
Training Time Requirement	None	High — requires thousands of episodes for stability and competence
Best Use Cases	Mobile games, deterministic environments, low-resource devices	Adaptive AI in sandbox or survival games, large PC/ console projects
Scalability	Easy to scale with many NPCs	Scaling requires memory optimization or Q-function approximators
Customizability	High — modular FSM state addition is straightforward	Medium — influenced by tuning rewards, α/γ/ε parameters
Intelligence Perception	Feels "Scripted intelligence"	"Learning agent" feel with less predictability

Table 3. Performance Metrics Summary for FSM and Q-Learning Agents

Metric	FSM + A*	Q-Learning
Average Catch Rate (%)	54.11	82.1 (after train)
Average Steps to Catch	24.9	13.2
Escape Rate (%)	45.89	17.9
F1 Score	0.84	0.88

DISCUSSION

The results name a number of key considerations for developers that will enable them to integrate advanced non-player character intelligence

Rule-based systems are the dependable workhorses of game AI. They provide good, predictable performance with decent development time. There's reassurance in knowing precisely how your NPCs will act in a given situation. But that predictability is a failing when players witness the same reaction repeated endlessly, resulting in that "I'm fighting robots" sensation that shatters immersion.

Reinforcement learning generates NPCs that truly surprise and learn but at the expense of increased development times and sometimes erratic behavior that can ruin carefully balanced gameplay.

Combined Methodologies

1. Employ A* and FSM for basic navigation and baseline behavior
2. Enhance tactical decision-making via layer reinforcement learning.
3. Let reinforcement learning discover best strategies while learning, and then bake most successful strategies into better systems.

Limitations and Challenges

When rule-based NPCs were bad, tracking down the cause was easy - simply trace the state transitions and you'll discover the bug. With reinforcement learning, debugging was more like detective work. "Why did the NPC just walk around in circles and not pursue the player?" We could have explained that in a matter of minutes using rule-based AI. Using reinforcement learning, sometimes the answer was hidden in neural network weights with no straightforward explanation.

It became increasingly difficult to introduce new behaviors to our FSM as the number of states grew. We had intertwined transition diagrams that were difficult to follow. Reinforcement learning managed behavioral complexity more effectively but suffocated when we included too many input features. The state space explosion rendered training times unrealistic.

There are numerous promising directions that can potentially break these constraints:

1. Picture being able to train a "generally intelligent" NPC that would learn seamlessly to fit into specific games or worlds. Transfer learning provides that - train once, fit anywhere. That would cut the training burden that makes reinforcement learning the state of the art today inaccessible to many development teams.
2. Current models are somewhat forgetful - they retain little historical context. Adding memory via recurrent networks or transformers, NPCs could potentially make long-term plans and recognize trends in player behavior over the long term. In a test with a basic memory system, our NPC learned to expect player action after a few encounters. This suggestion of "memory" created much more interesting encounters.

3. Imagine if NPCs could create models of individual players and adapt themselves to each one. This front of personalization might develop individually difficult experiences based on each player's skill level and style of play. We did a small pilot on this idea, where NPCs would be monitoring the level of player aggression and react accordingly. The aggressive players rushing in would be greeted with more defensive NPCs, and the cautious players would receive more aggressive ones. The players' reaction was highly positive.
4. Developer tools explaining why reinforcement learning NPCs choose certain actions would be worth their weight in gold. Decision processes displayed visually could revolutionize debugging from trial and error to enlightenment.

Practical Implementation Recommendations

According to our findings, the following is my advice to practice developers:

1. For single-player games or restricted schedules, use rule-based systems but spend time developing diverse state transitions
2. For AAA titles where NPC behavior is a market differentiator, reinforcement learning can produce truly differentiated experiences that are worth the investment
3. For mobile games, use reinforcement learning in development to learn best behaviors, then encode these as effective rule-based systems
4. Always consider your target hardware - reinforcement learning run can be light, yet not all platforms can handle complex models

CONCLUSION AND FUTURE SCOPE

This paper provides a comprehensive comparative analysis of conventional rule-based artificial intelligence and adaptive reinforcement learning techniques to Non-Player Character (NPC) behavior in video games. By systematic deployment and comparison of Finite State Machines (FSM) and A* pathfinding algorithms with Q-learning reinforcement learning in controlled grid worlds, we have measured the inherent fundamental trade-offs in these techniques. The FSM agent achieved a respectable catch rate of 54.11% with an average of 24.9 steps to intercept, showing consistent but limited adaptability, bound by its pre-defined logic and inability to learn from experience. The Q-learning agent, on the other hand, showed an initial learning phase with a success rate of merely 25-35%; however, it proceeded to achieve a catch rate of 82.1% with an average of 13.2 steps to intercept after around 2,000 training episodes. This spectacular improvement in performance was enabled through our novel application of a persistent Q-table, allowing cumulative learning across multiple gaming sessions—an invaluable innovation that mimics human learning behaviors in game environments.

The Q-learning agent demonstrated emergent behaviors such as path anticipation, strategic positioning, and adaptive trap-setting, which were not explicitly programmed in advance. This effect is demonstrated to be the capability of reinforcement learning to generate more interesting and dynamic non-player characters (NPCs). Yet, this adaptability came at the expense of higher computational complexity—characterized by $O(S \times A)$ space requirements compared to the $O(1)$ demands of finite state machines (FSM)—and significant training time, with steady performance only being realized after around 4.3 hours of training on our defined hardware. These results offer game developers key insights: FSM systems are most appropriate for mobile platforms, deterministic multiplayer synchronization, and projects constrained by limited development resources, whereas reinforcement learning provides greater adaptability for dynamic environments where constraints on training time and computational resources are low.

Looking ahead, a number of promising research areas stem from this work. The union of FSM's computational efficiency with RL's flexibility in hybrid frameworks offers a near-term potential—potentially through hierarchical systems in which FSM manages high-level state transitions and RL optimizes tactical choices within states. Deep Q-network integration to manage continuous state spaces and vision inputs may provide more advanced environmental awareness, and multi-agent reinforcement learning frameworks such as MADDPG may support coordinated group action and emergent social dynamics among NPCs. Moreover, application of real-time player skill estimation systems may provide dynamic difficulty adjustment, generating personalized challenge curves that adapt to player abilities and preferences. Transfer learning methods provide another way of minimizing training overhead by enabling pre-trained models to learn new game worlds or character classes rapidly. Lastly, creation of explainable AI tools specifically for game development may simplify the "black box" of learned behavior, giving

developers visual decision-making feedback essential to debugging and balancing game play. With consumer hardware changing and machine learning frameworks increasingly moving into the mainstream, we foresee these adaptive AI methods to influence increasingly the future of game development, producing more immersive, responsive, and personalized gaming experiences bridging the gap between scripted and intelligent behavior.

REFERENCES

1. J. Smith, "AI in Classic Arcade Games," Game Developers Conference, 2010.
2. J. Orkin, "Three States and a Plan: The AI of F.E.A.R.," Game Developers Conference, 2006.
3. D. Ashlock and J. Schrum, "Constructing Game Levels via Evolution," in Applications of Evolutionary Computation, Springer, 2009, pp. 311–320.
4. J. Togelius, G. N. Yannakakis, K. O. Stanley, and C. Browne, "Search-Based Procedural Content Generation: A Taxonomy and Survey," IEEE Transactions on Computational Intelligence and AI in Games, vol. 3, no. 3, pp. 172–186, Sept. 2011.
5. O. Vinyals et al., "Grandmaster level in StarCraft II using multi-agent reinforcement learning," Nature, vol. 575, pp. 350–354, 2019.
6. Unity Technologies, "Unity ML-Agents Toolkit," GitHub Repository, https://github.com/Unity-Technologies/ml-agents.
7. T. Schaul, "A Video Game Description Language for Model-Based or Interactive Learning," in IEEE Conference on Computational Intelligence and Games, 2013.
8. I. Horswill and M. F. Will, "Designing a Horror Game AI: A Case Study of Alien: Isolation," Game AI Pro 2, CRC Press, 2015.
9. M. Horsley, "The World Lives and Breathes: Immersive AI in RDR2," Game Developers Conference, 2019.
10. P. Hart, N. Nilsson, and B. Raphael, "A Formal Basis for the Heuristic Determination of Minimum Cost Paths," IEEE Transactions on Systems Science and Cybernetics, vol. 4, no. 2, pp. 100-107, 1968.
11. R. Sutton and A. Barto, "Reinforcement Learning: An Introduction," MIT Press, Cambridge, MA, 2018.
12. M. Filer, OpenCAGE: A tool to explore the files of Alien: Isolation, GitHub repository, 2021. [Online]. Available: https://github.com/MattFiler/OpenCAGE

A Hybrid Approach to Fine-Grained Multi-Emotion Sentiment Analysis of Google Reviews using SVM, Transformers, and Lexicon-Based Models

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ABSTRACT

Traditional sentiment analysis often misses the complex feelings present in user-generated content, like Google Reviews. It tends to focus on basic categories, such as positive, negative, and neutral. This study suggests a real-time sentiment analysis method that can recognize a range of emotions, including happiness, sadness, sarcasm, jealousy, and neutrality, by using a multi-model framework. To lay a strong groundwork for detecting emotions, we first apply Support Vector Machine (SVM) classifiers alongside TF-IDF to extract weighted features from cleaned English-only data. We also use pre trained transformer models like BERT and RoBERTa to boost classification accuracy for subtle sentiments by capturing contextual understanding and deeper meanings in the text. Our hybrid method combines machine learning classifiers with rule-based sentiment scoring. We use VADER and TextBlob to improve reliability and make results easier to interpret and modify. The research highlights the limits of traditional sentiment classifications and shows the benefits of using multiple methods in areas like political discussion, product evaluation, and mental health assessments. Future work will compare the performance of transformers in different languages and fields. We also plan to expand the system to analyze sentiment across various cultures and languages.

KEYWORDS *: Sentiment analysis, Emotion detection, Support vector machines, Natural language processing, Google reviews, TF-IDF vectorization, Pretrained transformers, Multilingual data, Fine-grained classification, Hybrid models, Machine learning.*

INTRODUCTION

The advent of digital platforms has changed the way we communicate, allowing ideas and feelings to travel easily across national borders. Public sites like Google Reviews offer significant opportunities for this public "opinion" sharing, and they contain vast amounts of user-generated public content that is rich in emotion. Exploring this content can provide some insight into public "sentiment" but it presents many difficulties. People's emotions are multifaceted and can be challenging to characterize correctly if they are complexly united by irony or other ways, and cultural significance compounds the challenges. The common use of basic methods for sentiment analysis, like determining whether reviews were positive, negative, or neutral run into basic challenges in third-party reviews. Google Reviews are a unique data source that is perfectly imperfect for advanced sentiment analysis, effortlessly encapsulating cultural diversity and language informality, and challenges from grammatical irregularities, and multilingual stimuli—the data source has the features to serve as a real-world test for a strong model.[2]

The study demonstrated a sentiment analysis system applying Support Vector Machines (SVMs). SVMs, as machine learning methods, would apply to these types of challenges in these specific situations if the analyst wants to preserve precious computational and time resources, are a competent choice for working with high-dimensional, sparse data, and they will work well for classifying several emotions using naive algorithm selections. In an offline capacity, this study and its content engaged a smart data pipeline designed for Google Reviews, including

automated data collection, language detection, removing irrelevant records, and cleaning the records (tokenization, lemmatization, filtration of unwanted terms). The cleaned review text was converted into numerical features output using TF-IDF which retains emotionally significant terms while filtering out generic terms. Apart from critical performance, disaggregating described emotions can also support mental health conversation monitoring, customer service potential, and build a space for emotionally cognizant AI systems.[1]

In contrast to classical algorithms, transformer-based models such as BERT (Bidirectional Encoder Representations from Transformers) and RoBERTa (A Robustly Optimized BERT Pretraining Approach) provide a state-of-the-art alternative for sentiment analysis by capturing deep contextual semantics and word dependencies. These models rely on attention mechanisms that evaluate the relationships between all words in a sentence, making them particularly well-suited for recognizing nuanced expressions such as sarcasm, indirect emotion, or domain-specific sentiment. In this study, pretrained transformer models were fine-tuned on the processed Google Reviews dataset, enabling transfer learning with minimal labeled data. The ability of these models to understand the subtle emotional tones and linguistic variations contributes to more accurate and robust classification, particularly for complex sentiment categories like jealousy or mixed emotions. While computationally intensive, their use is justified in applications where deeper language understanding and high predictive performance are prioritized over training speed or system simplicity.

To bridge the gap between interpretability and predictive power, a hybrid sentiment analysis method was implemented by integrating lexicon-based scoring systems (such as VADER and TextBlob) with traditional machine learning classifiers. This dual-layer approach leverages sentiment lexicons for their rule-based reliability in capturing polarity and subjectivity, especially in short texts, while allowing machine learning models to refine predictions based on contextual patterns. The hybrid pipeline was designed to score sentences on initial emotional tones using predefined sentiment dictionaries, and then feed these scores along with TF-IDF features into classifiers like logistic regression and decision trees for final emotion categorization. This method is computationally efficient and enhances transparency in decision-making, which is particularly valuable in applications like consumer feedback analysis, early warning systems in mental health, and content moderation. Its modularity also facilitates easy updates for multilingual or domain-specific use cases, offering scalability without compromising model interpretability.

RELATED WORK

Sentiment analysis has received significant attention over time, particularly in user-generated contexts like product reviews, social media, and blogs. Conventional sentiment analysis mainly used binary classification, dividing text into positive or negative sentiment. While efficient in limited settings, such strategies are not able to tap into the richness and complexity of human emotional expressions witnessed in real-world textual data.

To counter this limitation, some researches added nuance to sentiment analysis with ternary classification models (positive, negative, neutral). Even those are lacking in detecting more nuanced emotional categories like sarcasm, envy, or jealousy, which abound in unstructured text like Google Reviews.

Support Vector Machines (SVMs) have been heavily researched for sentiment analysis because of their strength in operating in high-dimensional and sparse feature spaces. In conjunction with TF-IDF vectorization, SVMs reveal consistent performance in dealing with difficult, nonlinear data distributions. Though SVM-based approaches excel in text classification, most approaches have been limited to binary or ternary tasks. Fewer studies have their application expanded to fine-grained, multi-emotion classification, particularly for noisy, real-world, and multilingual datasets. In addition, SVM-based sentiment models do not generally have the capability to dynamically capture emotional context or language-specific detail unless paired with sophisticated preprocessing techniques.

Current developments in natural language processing have witnessed a general adoption of pre-trained transformer models, especially BERT and RoBERTa, in sentiment analysis. Fine-tuned versions of these models on large sentiment datasets like IMDB, Yelp, and Amazon Reviews have surpassed conventional models by learning more complex contextual and semantic relationships. They are particularly good at understanding domain-specific terminology, sarcasm, and hedged sentiment. Comparisons to traditional classifiers such as Naïve Bayes and logistic

regression uniformly report greater accuracy, recall, and robustness for transformer-based models on a variety of benchmark datasets.

Complementary to these techniques are hybrid sentiment analysis methods, where the lexicon-based method (e.g., VADER, TextBlob) is combined with machine learning classifiers. These techniques have been proposed to combine the explainability and ease of rule-based scoring with the flexibility and predictive ability of statistical learning. Hybrid systems have special application in low-resource domains or domain-specific datasets, where training data is sparse or where rule-based sentiment cues are domain-specific.

In spite of these improvements, multilingual embeddings, machine translation, and emotion-intensity modeling are under-explored—especially in SVM-based and hybrid systems for fine-grained emotion recognition. Most models have either high accuracy in mono-lingual scenarios or insufficient interpretability for real-time use.

Our contribution lies in applying and comparing SVM-based, transformer-based, and hybrid lexicon-ML sentiment analysis models for multi-emotion classification. Focusing on Google Reviews, we overcome the difference between rudimentary sentiment classification and the growing demand for emotionally intelligent, context-sensitive NLP models by offering a comparative, scalable approach that can identify nuanced emotion expressions like lust, sarcasm, doubt, and shame.

METHODOLOGY (I)

With the aid of Support Vector Machines (SVMs), this section provides a comprehensive overview of the methodological strategy followed for creating a fine-grained sentiment analysis model based on the intricate nature of human feelings as expressed in online reviews. The procedure involves four pivotal steps: data acquisition, preprocessing, feature engineering, and multi-emotion classification..

Data Acquisition using serpAPI

In order to obtain real-time, accurate, rich, user-generated reviews, we fetch the information directly from the serpApi.

This real-time fetching provides a dynamic and scalable pipeline wherein sentiment analysis can be done on demand for any business or location listed on Google Maps.

Preprocessing and Linguistic Normalization

Raw user input review data is noisy by nature and differs with language, dialect, tone, and grammar.

- Lowercasing: Normalization of text input to lowercase to prevent duplication.
- Stopword Removal: Separating general non-informative words (e.g., "the", "and").
- Punctuation Removal: Separating unnecessary symbols.
- Lemmatization: Reducing words to base form (e.g., "crying" → "cry").
- Language Detection and Translation (Optional): Applying multilingual support to normalize non-English reviews through translation APIs to ensure uniform emotion modeling[4].

Feature Extraction Using TF-IDF

Textual data was converted to numerical features with Term Frequency-Inverse Document Frequency (TF-IDF). This captures the significance of a term in a document compared to the corpus.

- TF: Measures how frequently a term occurs in a review.
- IDF: Measures how unique or rare a word is across all reviews.
- TF-IDF Vectorization: Creates sparse matrices representing the weighted term significance, which serves as the input feature vector for classification.

This aids semantic significance so that the model concentrates on emotionally charged words [5].

Multi-Emotion Sentiment Classification Using SVM

Standard binary sentiment classifiers do not work for the variety of emotions used in actual reviews. Our system employs a multi-class SVM with a ternary sentiment view for every emotion. The approach involves:

- Emotion Taxonomy: Eleven basic emotions were taken into account — happiness, sadness, anger, fear, surprise, lust, envy, jealousy, sarcasm, shame, and neutrality. Each emotion is further classified into positive, negative, and neutral aspects based on context and intent [6].

Emotion Polarity Example

Table 1: Emotion polarity examples across positive, negative, and neutral contexts

Emotion	Positive	Negative	Neutral
Happiness	Joy in success	Happiness at others' failure (schadenfreude)	An unknown person's success
Sadness	Releasing sadness therapeutically	Depression or sorrow	Unknown context of sadness
Anger	Anger against injustice	Aggressive outburst	Generic frustration, no target
Lust	Passion for creativity or art	Obsession or exploitation	Detached attraction
Sarcasm	Humorous critique	Mockery or passive aggression	Ambiguous or Context irrelevant

SVM Strategy

- One-vs-Rest (OvR) SVM classification employed
- Each emotion class was represented with a ternary classifier..
- Hyperparameter tuning was performed through GridSearchCV with RBF kernel, C=1.0, and gamma='scale'.

Training was performed with a mix of publicly available emotion-tagged datasets (e.g., GoEmotions) and augmented manually tagged Google Reviews.

Evaluation and Metrics

The classification model was tested on a labeled test set using the metrics listed below:

- Precision, Recall, and F1-score for each emotion class.
- Macro and Micro Averages to record performance on imbalanced classes.
- Confusion Matrices were examined for every ternary dimension of emotion to determine trends in misclassification, particularly on hard-to-classify expressions such as sarcasm and shame.

Implementation Architecture

The whole system was deployed as a modular pipeline using:

- SerpAPI for real-time data acquisition.
- Scikit-learn for machine learning (SVM, TF-IDF, evaluation).
- NLTK and SpaCy for preprocessing and linguistic normalization.
- Flask or Streamlit frontend for interactive user input and visualization of emotion breakdown.

Analytical Insights

Upon evaluation across thousands of reviews:

- Complex emotions like sarcasm, envy, and jealousy exhibited high inter-class confusion, validating the need for a fine-grained emotion model.
- Users often express multiple emotions simultaneously, e.g., "I'm happy they failed because they deserved it", which contains happiness (negative) and sarcasm.
- The ternary model of emotion better accounted for subtle human responses than generic sentiment models.

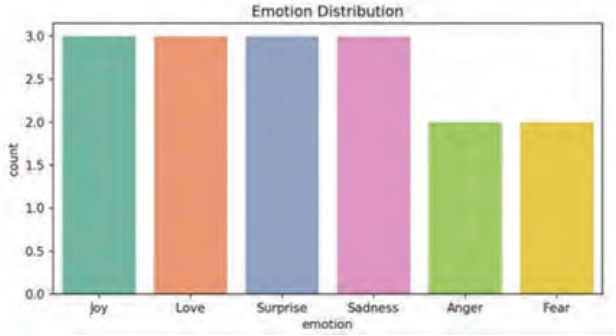

Fig. 1: The graph represents emotion distribution: Joy, Love, Surprise, and Sadness (3 each); Anger and Fear (2 each).

Advantages of SVM for Multi-Emotion Analysis

1. Superior Performance with High-Dimensional Data - SVM excels in the high-dimensional feature space created by different emotional expressions in Google Reviews, retaining effectiveness despite the large number of features.
2. Effective with Limited Training Data - SVM can achieve high classification accuracy even with small datasets, making it ideal for specialized emotion categories where labeled examples are limited.
3. Powerful Generalization - SVM's margin optimization property helps to avoid overfitting, allowing for accurate classification of previously unseen reviews with new emotional expressions.

4. Computational Efficiency - When combined with TF-IDF feature extraction, SVM provides fast classification times that are appropriate for real-time analysis of incoming Google Reviews.

5. Adaptability to Multi-Class Problems - Although SVM is naturally binary, it can be effectively applied to multi-class emotion classification using one-vs-all or one-vs-one methods.

Characteristics of the approach

1. API Integration Architecture - The system uses API to retrieve real-time review data, allowing for continuous analysis of new customer sentiment across multiple business classifications.

2. Multilingual Data Handling - The preprocessing pipeline of SVM handles the multilingual nature of the Google Reviews by preserving semantic content while standardizing inputs for the SVM classifier.

3. Fine-Grained Emotion Recognition - Unlike traditional binary or ternary sentiment models, our framework differentiates between nuanced emotional states (happiness, sadness, sarcasm, envy, jealousy, and lust), capturing the complexities of human expression.

4. Feature Representation Richness - TF-IDF vectorization maintains contextual word relevance while efficiently managing computational resources, balancing performance and processing requirements.

5. Real-Time Classification System - The end-to-end pipeline allows stakeholders to track sentiment shifts as they occur rather than conducting periodic analyses.

This analysis demonstrates the importance of modeling sentiment not as a binary or even single-label classification task but as a multidimensional, multi-polar emotional expression that varies with context and user perspective.

METHODOLOGY(II)

Pretrained Transformers (BERT and RoBERTa)

This section presents the methodology for employing transformer-based deep learning models to improve fine-grained emotion recognition from Google Reviews. The approach enhances semantic understanding by leveraging context-rich embeddings generated from pretrained models like BERT and RoBERTa.

Data Acquisition

Data was sourced using the same serpAPI-based real-time extraction pipeline as outlined in the SVM approach. All fetched reviews were stored in a structured JSON format, ensuring consistency across methods.

Preprocessing and Text Normalization

Minimal preprocessing was applied to preserve the linguistic richness required by transformer architectures:

Lowercasing and Punctuation Normalization were performed.

Emoji Conversion: Emojis were mapped to text using emoji libraries to capture affective signals.

Special Tokens Removal: HTML tags, URLs, and special characters were stripped.

Language Detection and Translation: Non-English reviews were translated using the Google Translate API to align with the English-only pretrained models.

Unlike traditional ML, steps like lemmatization or stopword removal were skipped, as transformers are sensitive to word positioning and syntax [7].

Tokenization and Embedding

Tokenizer: BERT/RoBERTa tokenizers from Hugging Face were used to convert text into subword tokens.

Embedding Representation: Input tokens were embedded using pre-trained weights (bert-base-uncased and roberta-base) and padded/truncated to a max sequence length of 128 [8].

Emotion Classification

The fine-tuning phase used the pretrained transformer model heads with a softmax output layer for multi-class classification:

Emotion Taxonomy: Same 11-emotion schema as the SVM model with ternary polarity (positive, negative, neutral) per emotion.

Multi-Label Output: Each review could express multiple emotions; a sigmoid activation allowed for overlapping classes.

Fine-Tuning Strategy:

Optimizer: AdamW Learning Rate: 2e-5 Epochs: 4

Batch Size: 16

Data: Combined GoEmotions dataset with labeled Google Reviews.

Model Adaptation: Separate fine-tuned models for BERT and RoBERTa were compared to evaluate performance gains.

Evaluation Metrics

The models were evaluated using:

Precision, Recall, and F1-score per emotion.

Hamming Loss to account for multi-label classification.

AUC-ROC for threshold analysis on each emotion's ternary classification [13].

Implementation Tools

Hugging Face Transformers for model architecture. PyTorch backend with GPU acceleration.

Streamlit Dashboard for interactive visualization of multi-emotion predictions and attention heatmaps.

WandB/MLflow for experiment tracking.

Observations and Insights

Transformers significantly improved the detection of context-dependent emotions such as sarcasm and shame.

BERT performed better with longer reviews; RoBERTa excelled in shorter, informal reviews.

Attention layers visually highlighted emotionally charged words, aiding interpretability.

Classification Report for BERT:

	precision	recall	f1-score	support
Negative	0.88	0.91	0.89	1629
Neutral	0.89	0.75	0.82	614
Positive	0.89	0.91	0.90	1544
micro avg	0.89	0.89	0.89	3787
macro avg	0.89	0.86	0.87	3787
weighted avg	0.89	0.89	0.88	3787
samples avg	0.89	0.89	0.89	3787

Fig 2: Classification report for BERT showing strong performance overall, with lower recall for Neutral sentiment.

Classification Report for RoBERTa:

	precision	recall	f1-score	support
Negative	0.91	0.89	0.90	1629
Neutral	0.74	0.84	0.78	614
Positive	0.92	0.88	0.90	1544
micro avg	0.88	0.88	0.88	3787
macro avg	0.85	0.87	0.86	3787
weighted avg	0.88	0.88	0.88	3787
samples avg	0.88	0.88	0.88	3787

Fig 3: Classification report for RoBERTa showing high performance overall, with lower precision for Neutral sentiment.

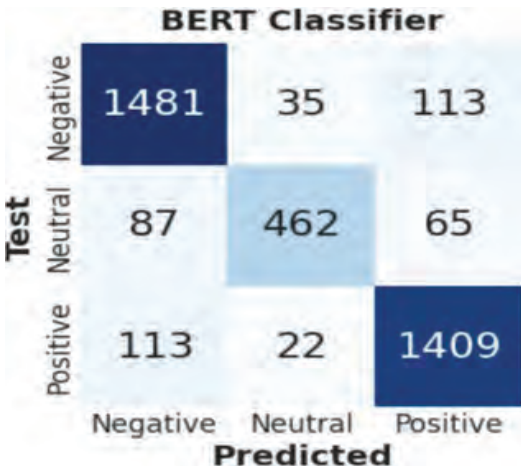

Fig 4: The BERT classifier predicts Negative and Positive sentiments well, but struggles with Neutral

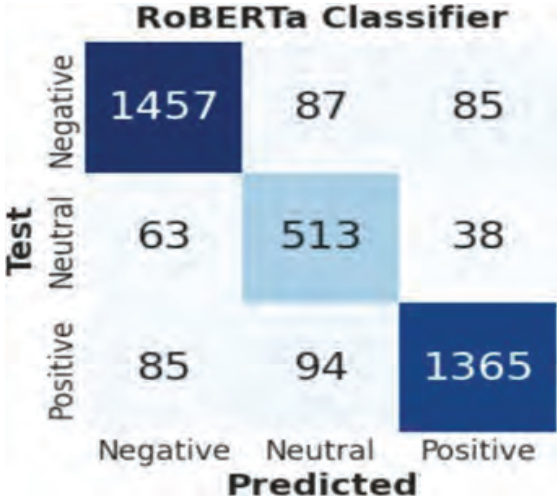

Fig 5: The RoBERTa classifier performs strongly across all classes, with improved Neutral sentiment prediction compared to BERT

Advantages of Pretrained Transformers for Multi-Emotion Analysis:

1. Contextual Understanding of Language

   Transformers like BERT and RoBERTa analyze text bidirectionally, allowing them to interpret subtle emotional cues, sarcasm, or ambiguous context more effectively than traditional models.

2. High Accuracy with Complex Emotion Classes Fine-tuning transformer models on emotion-tagged datasets enables precise classification across nuanced categories such as envy, shame, and sarcasm, which are challenging for conventional classifiers.

3. Transfer Learning for Low-Resource Domains

   Since transformers are pretrained on massive corpora, they can be fine-tuned with minimal labeled data, which is useful when annotated emotion datasets are limited or domain-specific.

4. Robust to Informal Language

   Transformers perform well on user-generated content (e.g., Google Reviews), which often includes misspellings, slang, and grammatical inconsistencies.

5. Multi-Label Emotion Detection

   BERT-based architectures can handle overlapping emotions in a single review by framing classification as a multi-label problem, capturing more realistic emotional compositions [15].

Characteristics of the Approach

1. Deep Learning-Based API-Driven System

   Integrates serpAPI for live review extraction, followed by a deep learning inference pipeline for real-time fine-grained emotion prediction using transformer backends.

2. Semantic Preservation for Multilingual Input

   Translated reviews retain semantic structure, enabling transformer models to detect context-specific emotions across languages using pre-fine-tuned multilingual BERT variants if needed.

3. Emotional Nuance Recognition

   Capable of identifying layered expressions (e.g., "I'm happy they failed") that involve contradictory emotions, providing more emotionally aware output than classical models.

4. Subword-Level Tokenization

   BERT's WordPiece tokenization manages out-of-vocabulary words and emotional modifiers, preserving meaning in informal or creative text structures.

5. Real-Time Emotion Dashboard

   Integrated with visualization tools (e.g., Streamlit) to show real-time emotion distributions, word-level attention maps, and temporal sentiment trends across categories.

METHODOLOGY(III)

Hybrid Lexicon-Based + Machine Learning Approach

This section outlines a hybrid methodology integrating rule-based lexicon sentiment scoring with statistical machine learning to balance interpretability and predictive strength for fine-grained emotion detection [9].

Data Collection

The same serpAPI-based review collection pipeline was used. Metadata such as language, timestamp, and location were retained for auxiliary analysis.

Preprocessing and Rule-Based Normalization Preprocessing involved

Lowercasing, stopword removal, and punctuation stripping.

Negation Handling: Rules for "not good" → "not_good" to preserve sentiment inversion.

Language Translation for multilingual inputs, ensuring consistent sentiment lexicon application.

Lexicon-Based Sentiment Scoring

Tools Used: VADER and TextBlob

Each review was scored across four sentiment attributes: Polarity (positive to negative)

Subjectivity (objective to subjective) Compound Score (VADER)

Emotion Keyword Count (from NRC lexicon)

These scores were aggregated and standardized into a feature vector for machine learning input.

Emotion Classification via ML

Classifiers Used: Logistic Regression, Decision Trees, and SVM were evaluated.

Features: TF-IDF vectors were concatenated with lexicon scores (hybrid vector).

Emotion Taxonomy: Same 11-class schema with ternary dimension.

One-vs-Rest Strategy: Individual classifiers for each emotion polarity.

Grid Search: Hyperparameter tuning on regularization and tree depth.

Evaluation Metrics

Model evaluation followed

Precision, Recall, F1-score per emotion. Confusion matrices for mixed-score reviews.

Interpretability Check: Model explanations using SHAP and LIME to assess the impact of lexicon vs TF-IDF features.

Technical Stack

NLTK, TextBlob, and VADER for rule-based scoring. Scikit-learn for ML models.

Pandas/Numpy for feature integration.

Flask Interface: Allowed users to toggle lexicon-only, ML-only, or hybrid scoring in real-time [11].

Observational Insights

Lexicon scores performed well for emotions like happiness and sadness.

Hybrid features improved precision in edge-case emotions like envy and lust.

Rule-based signals boosted interpretability, making this approach ideal for explainable AI use cases like healthcare or policy feedback.

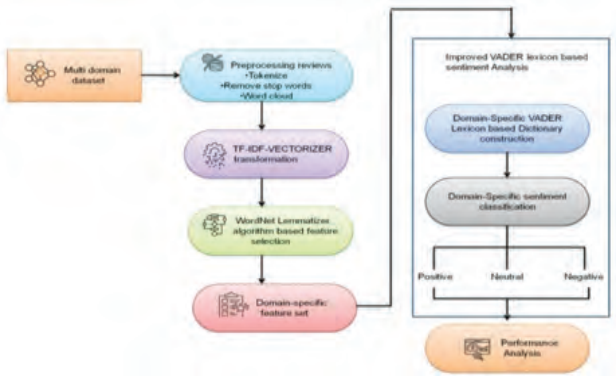

Fig. 6: Workflow of domain-specific sentiment analysis using improved VADER and feature engineering

Advantages of the Hybrid Lexicon + Machine Learning Approach for Multi-Emotion Analysis:

1. Interpretability and Explainability

Combining lexicon-based scoring with machine learning preserves transparency, making it easier for analysts and stakeholders to understand why a specific emotion was detected.

2. Efficient Feature Fusion

Lexicon-based features complement TF-IDF vectors by adding polarity, subjectivity, and emotion intensity scores, leading to more discriminative feature sets.

3. Strong Baseline Performance with Minimal Resources

Lexicon models (like VADER and TextBlob) can deliver reasonably accurate emotion estimates even in the absence of large labeled datasets, offering a lightweight alternative.

4. Adaptable to Domain-Specific Needs

Lexicons can be expanded or refined for domain-specific terms (e.g., hospitality, health), allowing for tailored emotion recognition without retraining the entire model.

5. Enhanced Performance on Straightforward Emotions

Emotions such as happiness, sadness, and anger are strongly associated with distinct vocabulary, making rule-based detection both fast and accurate.

Characteristics of the Approach:

1. Modular Architecture

A flexible architecture allows toggling between lexicon-only, ML-only, or hybrid modes — useful in resource-constrained or high-interpretability environments.

2. Multilingual Compatibility via Translation

Non-English inputs are normalized using translation APIs before applying sentiment lexicons designed for English, ensuring uniform feature scoring.

3. Emotion Scoring Layer

Preprocessing includes an emotion quantification layer that uses VADER compound scores, subjectivity index,

4. Lightweight Real-Time Scoring

Hybrid models run efficiently on CPU, making them ideal for deployment in dashboards or browser-based applications without significant computational overhead.

5. SHAP/LIME Integration

Model explainability is enhanced through SHAP or LIME, showing which words or lexicon scores influenced the final emotion classification.

APPLICATIONS

Its applications are diverse and influential in various fields. In mental health surveillance, it is able to pick up faint emotional signals, such as concealed anxiety in neutral speech or affect masking in distress, providing early alerts and more profound insights into patient welfare. It lays the groundwork for passive emotion monitoring and electronic triage for mental health [10].

Within customer service AI, interpreting multi-dimensional user emotions from feedback enables companies to provide more empathetic, emotionally intelligent, and richer responses. Instead of responding to binary satisfaction ratings, companies can anticipate frustration, sarcasm, or disappointment noted in reviews and support tickets.

To analyze public opinion, this model assists policymakers, researchers, and marketing professionals in diving deeper than superficial attitudes to identify collective emotional currents in groups. This allows for more effective decisions in fields such as public health initiatives, political communications, and crisis management [12].

For educational technology, identifying emotional engagement or bewilderment in students' feedback can assist teachers in adjusting their instructional design, individualizing learning, and enhancing student support systems.

In addition, creating empathetic chatbots and conversational AI is becoming more achievable. By using this multi-emotion classification model, chatbots can respond in a logical way and also show emotions. They can express understanding, concern, or encouragement when needed. This approach leads to more natural and human-like conversations.

Finally, in reputation monitoring and media analysis, companies may monitor brand perception not only by sentiment polarity but by detecting certain emotions such as anger, trust, envy, or sarcasm in various cultural and linguistic segments.

CONCLUSION

This study highlights the need for emotionally intelligent systems capable of interpreting complex human sentiments beyond binary classification. By integrating SVM with TF-IDF, transformer models (BERT, RoBERTa), and hybrid lexicon-ML approaches, we present a balanced, scalable, and interpretable framework for fine-grained emotion detection.

The system's ability to recognize nuanced emotions like sarcasm, envy, and doubt enables impactful applications in mental health, customer feedback, and public sentiment analysis. Future work may extend this by incorporating cross-lingual learning, multimodal inputs, and enhanced cultural sensitivity, paving the way for more human-aware and context-adaptive AI systems.

REFERENCES

1. Gede, I et al. "Comparison of Sentiment Analysis Algorithms with SMOTE Oversampling and TF-IDF Implementation on Google Reviews for Public Health Centers." MALCOM: Indonesian Journal of Machine Learning and Computer Science (2024): n. pag.
2. Wadhvani, Barkha A. et al. "Leading-Edge Sentiment Analysis: A Survey of Application Context, Challenges and Advanced Techniques." Recent Advances in Computer Science and Communications (2024): n. pag.
3. Silitonga, Christopher Alden Anugrah et al. "Comparative Study of BERT-CNN, TRANS-BLSTM, and RoBERTa Models for Sentiment Analysis." 2024 8th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE) (2024): 358-363.
4. Balande, Bharti B. et al. "Pre-processing Techniques for Performing Hotel Review Sentiment Analysis." 2023 2nd International Conference on Futuristic Technologies (INCOFT) (2023): 1-6.
5. Setiawan, Yudi et al. "Feature Extraction TF-IDF to Perform Cyberbullying Text Classification: A Literature Review and Future Research Direction." 2022 International Conference on Information Technology Systems and Innovation (ICITSI) (2022): 283-288.
6. Mouthami, Ms. K. et al. "Sentiment analysis and classification based on textual reviews." 2013 International Conference on Information Communication and Embedded Systems (ICICES) (2013): 271-276.
7.]Miah, Md. Saef Ullah et al. "A multimodal approach to cross-lingual sentiment analysis with ensemble of transformer and LLM." Scientific Reports 14 (2024): n. pag.
8. Erkan, Alı and Tunga Güngör. "Analysis of Deep Learning Model Combinations and Tokenization Approaches in Sentiment Classification." IEEE Access 11 (2023): 134951-134968.
9. Marshan, Alaa et al. "Sentiment Analysis to Support Marketing Decision Making Process: A Hybrid Model." (2020).

10. Wankhade, M., Rao, A.C.S. & Kulkarni, C. A survey on sentiment analysis methods, applications, and challenges. Artif Intell Rev 55, 5731–5780 (2022).

11.]J, Dr. Bhuvana. "A STUDY AND DEVELOPMENT OF APPLICATION ON SENTIMENT ANALYSIS." International Scientific Journal of Engineering and Management (2024): n. pag.

12. Bonifazi, Gianluca et al. "A framework for investigating the dynamics of user and community sentiments in a social platform." Data Knowl. Eng. 146 (2023): 102183..

13. Hassan, Saeed-Ul, Saleem, Aneela, Soroya, Saira Hanif, Safder, Iqra, Iqbal, Sehrish, Jamil, Saqib, Bukhari, Faisal, Aljohani, Naif Radi and Nawaz, Raheel (2021) Sentiment analysis of tweets through Altmetrics: a machine learning approach. Journal of Information Science, 47 (6). pp. 712-726. ISSN 0165-5515

14. Lange, Kathy and Saratendu Sethi. "What Are People Saying about Your Company, Your Products, or Your Brand?" (2011).

15. Rezapour, Mahdi. "Emotion Detection with Transformers: A Comparative Study." ArXiv abs/2403.15454 (2024): n. pag.

A Deep Learning Framework for Modelling Alzheimer's Disease Progression

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ABSTRACT

Alzheimer's disease is a progressive neurodegenerative disease characterized by decline in memory, thinking, and longitudinal behavioral changes. The disease processes that characterize the disease appear in severe and progressively detectable ways through the decline in neurological behavior with major implications on quality of life and strain on health care systems around the globe. This study introduces a new method using the ResNet- 50 deep learning model that has been fine-tuned for the unique objective of using the OASIS-1 dataset, as a demonstration in proving the feasibility of classifying the stage of Alzheimer's disease from neuroimaging data. We were able to show our fine-tuned model scored a 95.05% accuracy across classes of Alzheimer's disease stage from neuroimaging data. The ability to stage the disease as early as possible is particularly relevant for the clinical management of Alzheimer's disease because it creates an opportunity for interventions that can change the trajectory of the decline in behavior. Using the rich structural details preserved in the MRI scans, our ResNet-50 implementation leverages some of the most subtle yet significant changes in neuroanatomy to identify the stage of the disease. The performance we are seeing raises exciting possibilities that could be utilized in clinical workflows, in providing clinicians with a reliable, highly accurate tool to assess their patients. This study contributes to the family of computational methods aimed at improving the care of individuals with Alzheimer's through increased timeliness of detection, and better characterization of the disease, which ultimately strategizes better treatment and care for those that are affected.

***KEYWORDS** : Alzheimer's disease, Deep learning, ResNet-50, OASIS-1 dataset, MRI, Disease staging, Transfer learning, Medical imaging, Neurodegeneration, Classification.*

INTRODUCTION

Alzheimer's Disease (AD) is one form of neurodegenerative disease that results in a progressive loss of memory, intellectual function, and daily functioning. It is the most common type of dementia, responsible for 60-80% of all dementia illnesses [1]. What makes AD different from other neurodegenerative diseases is the accumulation of amyloid-beta (Aβ) plaques and tau protein tangles in the brain. These toxic accumulations disrupt communication among neurons, which eventually kills brain cells [6]. As the population worldwide continues to age, we can look forward to seeing a huge increase in the incidence of people who are diagnosed with AD, hence making early and proper diagnosis ever more important [2]. In its initial stages, AD can manifest as mild cognitive impairment (MCI), in which people may have minor memory loss or have difficulty with tasks that involve concentration and problem- solving. As the disease progresses, memory loss is more significant, language abilities deteriorate, and people have significant difficulty with judgment and decision- making. Advancements in deep learning and artificial intelligence (AI) have been shown to have excellent potential for the early staging and prediction of AD, using non-invasive type data sources such as Magnetic Resonance Imaging (MRI) [7-8]. These techniques have the ability to recognize subtle transformation in brain structure and function that can promote early intervention and enhance patient care. The

integration of artificial intelligence and deep learning is critical for the challenges of early diagnosis and stage prediction of AD because it would aid in the exploitation of enormous amounts of advanced non-invasive data to reengineer the early diagnoses of AD [6]. The ability to predict the stage of Alzheimer's disease in an appropriate manner could remarkably improve patient management and treatment, allowing for early intervention and better care [7-8].

Deep Learning for Alzheimer's Disease

The advancement in Machine Learning and, specifically, in Deep Learning enables us to construct models that learn directly from data with minimal pre- processing and considerable domain knowledge from subject matter experts. Deep learning methods, like Convolutional Neural Networks, Recurrent Neural Networks, and Autoencoders, have demonstrated remarkable success in several medical imaging applications, such as the diagnosis and stage prediction of Alzheimer's Disease [7]. Recent research has delved into applying deep learning models to the early diagnosis of Alzheimer's Disease with structural Magnetic Resonance Imaging data [3,5]. The models have been shown to be able to identify AD patients or those who are likely to develop the disease, even at an early stage. In addition, deep learning-based models have been created to predict the progression stage of Alzheimer's Disease so that monitoring and management of the disease can be more accurately achieved [4].

Background

Alzheimer's Disease is a multi-dimensional neurological condition that impacts thinking and memory functions. Early diagnosis, especially of the prodromal stage of Alzheimer's Disease such as Mild Cognitive Impairment (MCI), is essential for appropriate and timely treatment [3]. Current diagnostic procedures rarely have adequacies in sensitivity, specificity, and cost. Deep learning models trained with seMRI and PET imaging have been more accurate than existing applications. because they can model the complex habits of the disease [9]. Using strategies such as sharpness-aware minimization (e.g., SA-ERM) produces models that are more reliable for application in clinical settings. In addition, the use of speech and text-based deep learning with natural language processing (NLP) is now a prominent strategy for detecting cognitive impairment using linguistic markers as indicators of impairment [10]. Taking a multimodal approach for accurate and early detection of AD and serious cognitive impairment, offers a promising low-cost solution.

LITERATURE ANALYSIS

Prediction and classification of Alzheimer's disease (AD) through computational approaches greatly depend on extensive, well- documented datasets and novel analytical tools. Two of the most influential datasets in AD research are the Open Access Series of Imaging Studies (OASIS) and the Alzheimer's Disease Neuroimaging Initiative (ADNI).

Foundational Neuroimaging Datasets: OASIS and ADNI

The OASIS (Open Access Series of Imaging Studies) project provides open-access MRI datasets with a primary focus on cross- sectional T1-weighted scans (OASIS-1) and longitudinal data (OASIS-2, OASIS-3), as well as demographic and cognitive data [15, 16]. OASIS's structured and standardized MRI data makes it well-suited for the development of structural biomarkers and early predictive classification models. In contrast, the Alzheimer's Disease Neuroimaging Initiative (ADNI) is a large multi-site longitudinal study which has provided a wealth of data (MRI, PET, CSF biomarker, genetics, cognition) - in a multi-modal way - so that the same study subjects can be tracked over time [17–19]. OASIS is excellent for use in developing early models, whereas ADNI is excellent to explore full disease evolution of Alzheimer's over time and discover preclinical biomarkers via a rich multi- modal dataset. [19]

Methodological Advancements in AD Classification and Prediction

Recent research leverages these datasets and others to explore various computational approaches for AD diagnosis and prediction.

Deep Learning with Neuroimaging Data

Deep learning, especially Convolutional Neural Networks (CNNs), has become an important approach to neuroimaging analysis. Jansi et al. (2023) used OASIS-1 with 2D slices (of 3D MRI) and supplemented this approach with SMOTE and brightness normalizing, reaching 87.69% accuracy using InceptionV3 for multi-class AD classifying [12]. Sisodia et al. (2023) were able to show adaptability by using DenseNet201 on ADNI-MRI data [20]. Hu and colleagues (2023) advocated for new transformer- based architectures by introducing their hybrid VGG- TSwinformer model for predicting MCI-to-AD conversion [21].

Machine Learning and Diverse Biomarkers

In addition to traditional CNNs on MRI, other machine learning methods and modalities of data are investigated by researchers. Rao et al. utilized conventional machine learning models such as Multilayer Perceptrons (MLP) and Support Vector Machines (SVM) on 3D MRI data to separate AD from cognitively normal subjects, as classical methods to classification [22]. Bermudez et al. examined the predictive value of plasma biomarkers, such as Aβ42/40 ratio, p-tau181, GFAP, and NfL, based on data from a prospective population-based study. This is an increasing interest in minimally invasive fluid biomarkers for prediction of AD [23]. Jiao et al. emphasized EEG biomarkers in a large sample set comprising MCI, AD, other dementias, and healthy controls and illustrated the promise of functional brain activity measurements obtained through EEG for differential diagnosis [24].

Genetic Factors and Advanced Modeling

Genetic data is essential to AD research. For instance, Gustavson et al. examined AD Polygenic Risk Scores (AD-PRSs) in a large male cohort in relation to cognitive outcomes [25] and Shigemizu et al. examined genes related to immunity and renal disease in patients with late-onset AD (LOAD) to find potential genetic risk factors [26]. Parisot et al. even used sophisticated models such as Graph Convolutional Networks (GCNs) to incorporate imaging and non-imaging data and to capture complex patterns of disease [27]. Hoare et al. further illustrated the significance of employing a study dedicated to early AD detection, emphasizing early detection [28].

Table 1. Research Contributions in Alzheimer's Classification

Sr. no	Authors & Study	Model/ Technique	Dataset	Classes Consi-dered
1	Jansi et al. (2023) [12]	SMOTE + InceptionV3	OASIS-1	Non-Demented, Very Mild, Mild, Moderate
2	Rao et al. [22]	MLP/SVM	3D MRI	AD vs. Cognitively Normal
3	Sisodia et al. (2023) [20]	DenseNet201	MRI (ADNI)	Early-Stage AD, Moderate AD, Non-Demented
4	Hu et al. (2023) [21]	VGG-TSwinformer	ADNI	MCI Converters vs. Stable
5	Gustavson et al.[25]	AD-PRSs score calculation	1,168 men data	Cognitive Normal
6	Bermudez et al. [23]	AŒ≤42/40 ratio, p-tau181, GFAP, and NfL	Prospective population-based study involving 350 participants	AD Prediction
7	Jiao et al. [24]	EEG biomarkers	890 participants (MCI, AD, other dementia forms, and healthy controls)	MCI, AD, other dementia forms, and healthy controls
8	Shigemizu et al. [26]	Major risk genes and immune-related genes, genes related to kidney disorders	LOAD patients	LOAD patients
9	Parisot et al. [27]	Graph Convolutional Networks (GCNs)	Combined imaging and non-imaging data	Disease Prediction
10	Hoare et al. [28]	Early detection study	Unspecified	AD

METHODOLOGY

Dataset Description

By making brain imaging data publicly available, the Open Access Series of Imaging Studies (OASIS-1) makes a substantial contribution to the neuroscience research community. Researchers looking into Alzheimer's disease, cognitive decline, and normal aging will find this collection to be a useful resource.

Dataset Overview and Collection

OASIS-1 is a cross-sectional dataset with 416 subjects aged between 18 and 96 years[16][29]. Principal investigators D. Marcus, R. Buckner, J. Csernansky, and J. Morris created the dataset, and released it for the first time to the scientific community in 2007[16,30]. Funding was provided by several grants: P50 AG05681, P01 AG03991, P01 AG026276, R01 AG021910, P20

MH071616, and U24 RR021382[16]. All subjects in the OASIS-1 dataset were scanned in a single scanning session where 3-4 separate T1-weighted MRI scans were

acquired[16][29]. Participants were all right- handed and composed of both men and women from a variety of age groups[16]. Of critical importance to Alzheimer's research, 100 of the subjects above the age of 60 were clinically diagnosed with very mild to moderate Alzheimer's disease (AD)[16][29]. Moreover, the dataset also has a reliability factor with

20 non-demented participants who had a repeat imaging session within 90 days of their baseline scan so researchers can measure test-retest reliability over time[16][29].

Participant Demographics

The OASIS-1 dataset provides a comprehensive representation across the adult lifespan, with demographic information including:

Table 2. Oasis-1 Dataset Review

Age Group	Total Subjects	Male	Female	CDR 0.5/1/2
18-96 years	416	134	282	100 subjects

The dataset includes subjects with varying levels of cognitive function as measured by Clinical Dementia Rating (CDR), Mini- Mental State Examination (MMSE) scores, and normalized whole brain volume measurements (nWBV)[31][32]. Educational background and socioeconomic status information is also recorded for participants, providing additional context for analysis[31].

Kaggle Dataset Processing

We worked with the preprocessed OASIS-1 neuroimaging dataset provided on Kaggle[33]. This version includes brain MRI data that has been preprocessed to make it easier to use for machine learning and deep learning purposes. Kaggle's version offers a transformed version of the original OASIS-1 dataset, with the intricate 3D MRI volumes being simplified to 2D image slices. Each volumetric brain scan was sectioned in a systematic way along standard anatomical planes (axial, sagittal,or coronal), producing a sequence of 2D cross-sectional images. This preprocessing scheme retains the structural information necessary and renders the data amenable to standard 2D image analysis methods. This preprocessed format considerably reduces technical barriers for researchers interested in 2D image analysis methods and facilitates easier use of standard computer vision algorithms to neuroimaging data.

Research Applications

OASIS-1 dataset is an essential source for early Alzheimer's detection, normal aging analysis, and neuroimaging-based machine learning research. It facilitates brain volumetric studies across demographics as well as supplying normative clinical information. Being an open-access movement, it facilitates worldwide scientific exchange by providing high-quality MRI data to researchers independent of their resources at a given institution. First presented in the Journal of Cognitive Neuroscience (Marcus et al., 2007) [16], OASIS-1 continues to be an essential resource in neuroscience research.

Oasis-1 Based Studies

We have done an exhaustive survey of previous outstanding work that used the OASIS-1 dataset to classify Alzheimer's disease. The comparative studies illustrated in the table are outstanding contributions that shaped our strategy. Islam & Zhang (2018)[11] and Jansi et al. (2023) [12] used raw MRI images from the OASIS- 1 dataset as inputs to their respective deep neural networks, thereby showcasing the efficacy of utilizing these neuroimaging scans for classification. To the contrary, Basheer et al. (2021)[14] approached this by first extracting useful information from OASIS-1 MRI images and then providing these extracted features as input to their network. These experiments are different methodological solutions to the same fundamental clinical problem, and they serve as useful context for our work and demonstrate the flexibility of the OASIS- 1 dataset across various machine learning frameworks.

Table 3. Comparative Analysis of OASIS-1 Based Studies

Sr no	Paper	Model Used	Classes	Accuracy
1	Islam & Zhang, Brain Informatics (2018) [11]	Ensemble of Deep Convolutional Neural Network (CNN)	Non-demented, Very mild, Mild, Moderate	93.18%
2	Basheer et al., IEEE Access (2021) [14]	Modified Capsule Network(M-CapNet)	Demented, Non-demented	92.39%
3	Jansi et al.,ICECA IEEE Conference (2023) [12]	Inception V3(with learning transfer and SMOTE)	Non-demented, Very mild, Mild, Moderate	87.69%

Proposed Model

The proposed model structure, shown in the figure, employs structural MRI scans to identify the phases of Alzheimer's

disease (AD) by means of a systematic and modular deep learning process. T1-weighted axial cuts of the OASIS-1 database form the input of the model. As axial projections provide an invariant cross- sectional view where one can observe early-stage neurodegeneration, these 2D slices are extracted from 3D MRI volumes. In order to provide a uniform input shape of (128, 128, 3), the slice is resized to unified resolution of 128×128 pixels and represented in RGB color with 3 channels.

This ensures major brain anatomy is retained without compromising that the entire images match the dimensionary demands of ResNet-50 [13]. The input images undergo a rigorous data augmentation step to counter the challenges posed by the relatively small size of the dataset and to promote generalization. This dynamic augmentation involves zooming within a range of ±15%, translations, random rotations of up to

±72 degrees, horizontal flipping, and minor contrast changes. By introducing controlled variability that simulates true acquisition conditions, such as scanner variations or patient movement, such augmentations add more visual context variety to the training set. The preprocessing layers of TensorFlow are used to incorporate the augmentation layer directly within the model pipeline so that it can perform real-time GPU acceleration transformations in the training process [13] [11]. Following augmentation, the images are fed into the main feature extractor, the ResNet-50 model. ResNet-50 is a 50- layer deep convolutional neural network that was initially trained on ImageNet. It is famously known for employing residual connections, which facilitate easier training of extremely deep networks without suffering from vanishing gradients. Only the convolutional base of ResNet-50 is retained in this architecture; the fully connected classification head is removed. This enables the model to recognize notable hierarchical features of brain MRI slices such as ventricular enlargement, cortical thickness, and hippocampal atrophy—biomarkers closely associated with various stages of Alzheimer's disease [13] [11].

The ResNet-50 backbone's output feature maps are then fed into a Global Average Pooling (GAP) layer. In contrast to flattening, which increases the dimensionality of the feature space, GAP represents each feature map by its average activation, yielding a compact and spatially invariant 2048-dimensional feature vector. Preserving necessary discriminative features needed for classification [1], this operation significantly reduces the number of trainable variables and serves to hinder overfitting. A two dense layer specially designed classifier head takes this feature vector as input.

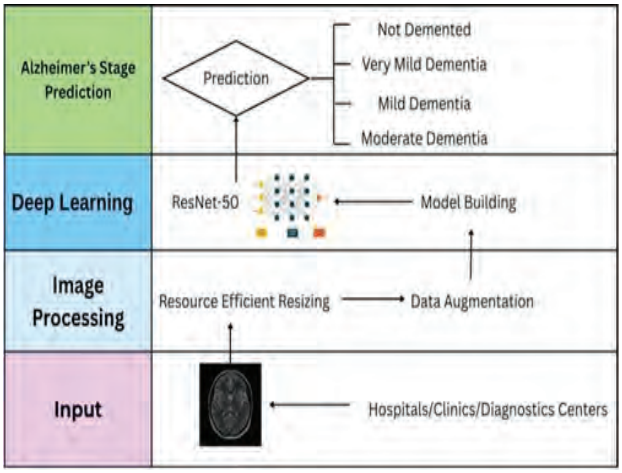

Fig. 1: Block Diagram of Proposed Architecture

The first dense layer consists of 512 neurons and uses the ReLU activation function. Batch normalisation and a dropout layer with a 40% regularisation rate follow. The second dense layer contains 256 neurons with batch normalisation, dropout of 30%, and activation of ReLU. The layers help the model to learn complicated non-linear feature representations specific to Alzheimer's disease without sacrificing robustness and against overfitting. The final output layer comprising four neurons provides class probabilities by activating the softmax activation function. One of the stages of Alzheimer's—non- demented, very slightly demented, mildly demented, and moderately demented—is exemplified by each of these neurons [13]. The figure does not display the two-stage process applied during training. The base layers of the ResNet-50 are frozen for the first step, and only the classifier head is trained.This preserves the general characteristics acquired from natural images but allows for fine-tuning of the newly added layers to adapt to the medical imaging context. The top 20% of the ResNet-50 layers are left unfrozen during the second phase to enable deeper convolutional filters to be fine-tuned to observe finer patterns related to Alzheimer's disease. For the purpose of ensuring gradual and constant convergence, there is a low learning rate during this phase. Applied to a highly specialized problem like AD stage classification, such phased training will allow effective transfer of knowledge from a general dataset [13][11].

Proposed Methodology with ResNet-50 model

This section details the procedures followed for data preparation, model construction, and training for the classification of Alzheimer's disease stages using MRI scans from the OASIS-1 dataset.

Data Preprocessing

The first step was configuring the MRI image data into a format suitable for use in a deep learning model. Using the class folders, images were fetched, and with PIL, they were resized to the standard dimensions of 128x128 pixels. The resized images were then changed to NumPy arrays. As stated before, a fundamental initial step was to ensure that every image array had three colour channels which are (128,128,3) shaped. Those images which could not meet this requirement were discarded from the dataset. To prepare the analysis, label encoding was applied to turn the category labels of "Non Demented," "Very Mild Demented," "Mild Demented," and "Moderate Demented" into numericals. The last label vector y for training was converted to contain these integer representations of the classes once categorical labels were converted to numerical indices (0 to 3). The sparse categorical cross-entropy loss function utilized subsequently in the model. The sparse categorical cross-entropy loss function utilized subsequently in the model training process is compatible with this integer form. Large NumPy arrays were formed by merging the processed image arrays (X) with the integer labels (y) that belonged to them. Finally, a shared data splitting utility was utilized in order to split the entire dataset into training and test subsets. To split 80% of the data for training purposes and 20% for testing, the data was split 80%-20%.To ensure that the proportion of each class was maintained in the training and testing sets, the split was sample shuffles and class-label stratification. To guarantee reproducibility, a fixed random seed was used during splitting.

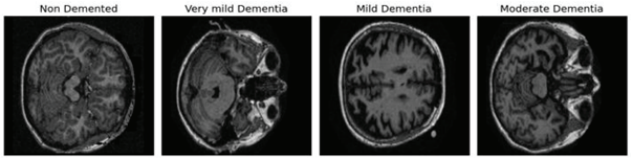

Fig. 2: Class-Wise MRI Representations of Alzheimer's Disease

Data Augmentation

In medical imaging where datasets are exceptionally small, the model's generalization ability along with the generalization of overfitting needs to be managed very carefully because it can inhibit the model from performing well with unseen data. In an effort to achieve this with the particular model, 'on- the-fly data augmentation' was employed to refine the model performance imbalance. Data augmentation techniques incorporated included random rotations (max of 72 degrees), random translations (vertically and horizontally moving by a max of 15% of image sizes) random zooming (by max 15%), random horizontal flips, and modifications to contrast (change of max 10% from original). This augmentation pipeline is constructed through computational graphs and therefore enables adding augmentation sequences directly to the model before the main feature extraction network.

Model Building

A transfer learning technique was utilized leveraging the ResNet- 50 model for base classification, which is well known for its intricate feature extraction capabilities on ImageNet. The architecture of the model contains an input layer which takes in tensors of size (128, 128, 3). The data augmentation pipeline as noted earlier has already processed this input. Later, the proper augmented tensors are supplied to the ResNet-50 base model from which the top classification layer has been removed. This base model is used purely as a feature extractor, augmenting tensors with pre-trained weights from ImageNet.

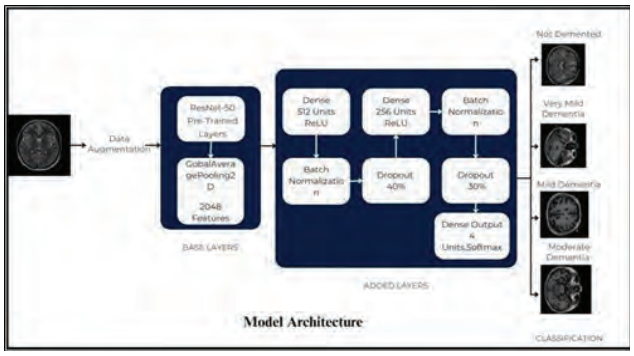

Fig. 3: Proposed Fine-tuned Model (ResNet-50) Architecture

A global average pooling layer (GlobalAveragePooling2D) was added after the convolutional base. This layer transforms the ResNet- 50 feature maps into a fixed-size feature vector (size 2048) by shrinking their spatial sizes. This kind of pooling promotes spatial invariance and significantly reduces the number of trainable parameters. This pooled feature vector was then augmented with a bespoke classifier head. This head consists of a 40% regularization dropout layer, batch normalisation to

improve training stability, and a dense layer of 512 units and ReLU activation. It is repeated using a dropout layer with a 30% rate, a further batch normalisation layer, and a dense layer of 256 units (ReLU activation). A softmax activation is employed to make class probability estimations in the last output layer, which consists of a four-unit dense layer, representing the four types of Alzheimer's disease. One computation graph model was developed by composing the entire model, from the initial input layer to the last output layer.

Training Strategy

A two-phase training plan was designed to leverage pre-trained weights and fine-tune the model to the specific task of Alzheimer's classification from OASIS MRI scans.

a. Phase 1: In this first phase, only the new custom classifier head was tuned. All layers of the ResNet-50 base model were frozen; they could not be updated with their weights. Sparse categorical cross-entropy loss, Adam builder, a starting learning rate of 1×10−3, and accuracy as a metric to evaluate the model were all used to compile the model. The training was carried out with batch size 32 for a maximum of 15 epochs. Significant training aids were employed in this phase including a routine that either automatically reset the model weights to the best epoch or stopped training if the validation loss did not improve for 7 consecutive epochs. Additionally, the learning rate was dynamically reduced by a factor of 0.2 whenever the validation loss had stopped improving for 3 epochs to prevent the learning rate from going below the minimum of 1×10−6. To assess performance and apply these training adaptive mechanisms, 20% of the training data were set aside for validation studies during that training process.

b. Phase 2: In the fine-tuning stage, the model required modification. The ResNet-50 base model's first 80% of layers were frozen in this stage, while the first 20% were unfrozen to allow these weights to be adjusted alongside the weights in the classifier head.

After changing the trainability of these layers, the model required recompilation. Similar to when using the fine-tuning stage, it was compiled using Adam when the training model was compiled, but this time with a learning rate of 1×10-4 to allow for smaller, and therefore more stable, adjustments to the pre- trained weights. The same metrics and loss function as the previous stage were not changed. The same mechanisms for learning rate reduction and early stopping were used. We fine-tuned the model up to twenty epochs with a batch size of sixteen and the same 20% validation split from our training set / training procedures.

This two-stage approach provides an opportunity for the model to gradually adjust the deeper, pre-trained features to the nuances of the target medical imaging domain, after first learning the task- specific, finer details captured in the weights of its classifier head. The final trained model was to use the best weights found throughout the training process and evaluate performance.

RESULTS AND DISCUSSION

Model evaluation matrix

To assess how good the model was at classification to stage the disease of Alzheimer's, we utilized the classic measurement tools: Precision, Accuracy, Recall or Sensitivity, and F1-Score. All these give broad measures of each stage's prediction strength as well as accuracy in correct identification by the model.

Accuracy:

$$\frac{TP+TN}{TP+TN+FP+FN}$$

Accuracy is the reliability of the model's positive predictions for a certain Alzheimer's stage.

It determines the proportion of true positive predictions among all the instances predicted as positive and thus reflects how well the model does not make incorrect positive predictions.

Precision

$$\frac{TP}{TP+FP}$$

Precision indicates the reliability of the model's positive predictions for a given Alzheimer's stage. It calculates the proportion of true positive predictions among all instances that were predicted as positive, thus reflecting the model's ability to avoid false positives.

Recall

$$\frac{TP}{TP+FN}$$

Recall quantifies how accurately the model is able to identify all the actual positive instances of a particular stage of Alzheimer's. It estimates the percentage of actual stage-specific instances the model accurately identified without giving any false negatives.

F1- Score

$$\frac{2TP}{2TP+FP+FN}$$

The F1-Score provides a harmonic mean of precision and recall, offering a single metric that balances both. It is particularly useful in scenarios with class imbalance, where optimizing either precision or recall alone might not provide a full picture of model performance.

Results of proposed model

Model Accuracy Plot & Model Loss Plot: Figures 4 and 5 show the training curve of the fine- tuned ResNet-50 model and report that accuracy and loss both increased consistently over the course of the 20 epochs. The training accuracy increased from around 80% to a high of 95.53%, and the validation accuracy also rose to 94.68% (nearly as high).The loss for validation only had minimal fluctuations during certain epochs but was quite stable and flattened out below 0.18 by the final training. From these patterns, there seems to have been good learning on the part of the model and no major overfitting. This can also be inferred from the training loss, which reduced steadily from about 0.45 up to a high of 0.12. The two-step training methodology for training the custom classifier head separately and subsequent fine-tuning of the remaining higher layers of the ResNet-50 base and slight (potential) class imbalance in training data probably facilitate generalization by the model well without overfitting. Overall, the training as well as the validation curves reveal a nice extent of convergence with the ability to generalize on unseen validation data.

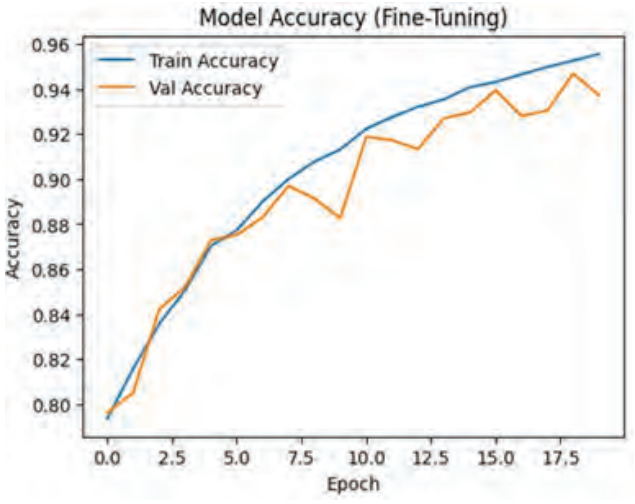

Fig. 4: Model Accuracy (Phase 2)

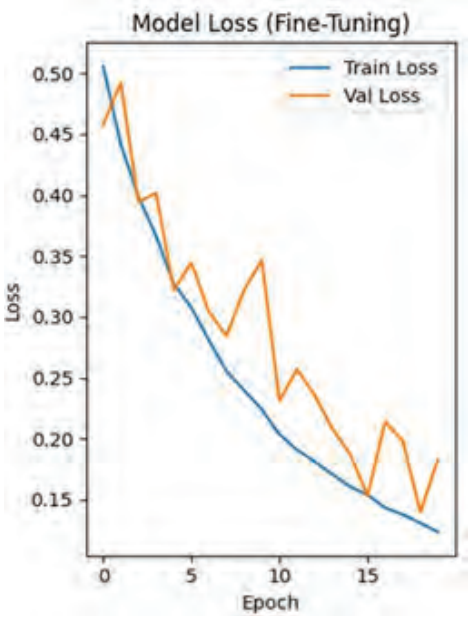

Fig. 5: Model Loss (Phase 2)

Table 4. Performance of proposed model

Class	Precision	Recall	F1-Score	Support
Non-demented	0.97	0.98	0.97	13,445
Mild	0.94	0.90	0.92	1,000
Moderate	0.86	0.99	0.92	98
Very mild	0.88	0.84	0.86	2,745
Average	0.95	0.95	0.95	17,288

Table of Proposed Model Accuracy

As shown in this table, the Proposed Model achieves high performance across all classes, with particularly strong Precision and Recall for the Non-Demented class and an overall average F1- Score of 0.95, indicating robust classification capability.

Confusion Matrix

The confusion matrix illustrates positively solid classifications in all four dementia categories: Non-Demented, Very Mild, Mild, and Moderate Demented. This suggests that our model was successful at differentiating between dementia classes. Non- Demented and Very Mild cases were easily differentiated, while some confusion arose due to the early-stage impairments felt at the onset of dementia; with early stages typically being much more subtle than naive cases. Mild Demented cases were classified accurately and emphasized the models capacity

to identify cases of mid-stage impairment. Moderate Demented predictions were reliable samples but were more limited in sample size. If genetic testing identified cases of Moderate Dementia with the same reliability as Non-Demented or Mild, the prediction performance would also improve with samples available within the moderate classification. In summary, the confusion matrix denotes the success of the model but also exhibits needs for future improvement related to "early- stage" differentiation, as well as the inclusion of samples across all dementia classes to achieve a more balanced distribution.

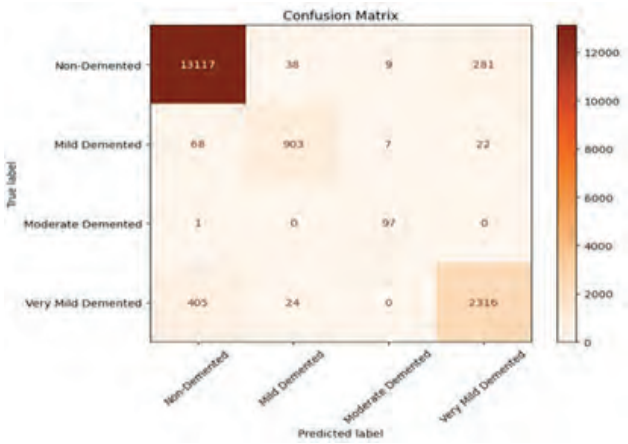

Fig. 6: Confusion Matrix of Proposed Model

As shown in the Confusion Matrix, the Proposed Model demonstrates strong classification performance, especially for the Non-Demented and Very Mild Demented classes, with most predictions correctly aligned with the true labels and minimal misclassifications.

Comparison of Results of Proposed Model with Existing Algorithms

Table 5 presents a comparison of the performance of these three models, Ensemble of Deep CNNs, InceptionV3, and Our Proposed Model, using Accuracy, Precision, Recall, and F1- Score. The Proposed Model achieved the highest accuracy of 95.05% compared to the Ensemble of Deep CNNs with 93.18% and InceptionV3 with 87.69%. The Proposed Model had the highest Precision with 95.17% compared to the Ensemble of Deep CNNs with 92.58% and and InceptionV3 that scored between 89– 100%. In Recall, the Proposed Model achieved 95.16%, while the Ensemble of Deep CNNs scored 93.18% and InceptionV3 scored between 75–100%. The F1-Scores demonstrated a similar trend: Proposed Model (95.0%), Ensemble of Deep CNNs (92.83%), InceptionV3 (77–100%).

Table 5. Comparison of Results with our Proposed Model

Model Name	Accura cy (%)	Precision (%)	Recall (%)	F1-Score (%)
Ensemble of Deep CNNs [11]	93.18	92.58	93.18	92.83
Inception 3 Model [12]	87.69	89– 100 (class-wise)	75–100 (class-wise)	77– 100 (class-wise)
Proposed Model (ResNet-50)	95.05	95.17	95.16	95

Therefore, the Proposed Model was shown superior to the other models on all metrics reviewed. These results demonstrate the robustness of Our Proposed Model and that it performed well across all metrics therefor provides a balanced classification for the task.

CONCLUSION

In this study, we put forth a method for the early detection and staging of Alzheimer's Disease by way of a fine-tuned ResNet-50 deep learning architecture. Our model was able to classify the various stages of AD with a 95.05% accuracy utilizing the OASIS- 1 dataset. This accuracy shows that residual neural networks are an effective approach for the accurate classification of subtle neuroanatomical changes throughout the progression of Alzheimer's Disease. Furthermore, the accuracy of classifying the four levels of Alzheimer's Disease (non-demented, very mild, mild, and moderate) while classifying with our ResNet-50 demonstrates considerable potential as a part of a clinical decision support system for clinicians during the diagnosis process. Even with promising results, there are limitations to this study. The use of 2D slices rather than the original volumetric data has inherent limitations; 3D data could have pointed end- users towards critical spatial context that was simply not available in the 2D representation. Image quality impacted performance with regard to both temporary camel images and deeper issues related to preprocessing, suggesting preparation of the images may yield better models in future. The reliance on OASIS -1 is also a constraint in respect of generalisability. Future work will expand on these findings through 3D convolutional networks, including multimodal data such as MRI with PET imaging at later stages of the project, while using explainable AI that provides broader clinical interpretation of results. In conclusion, this study provides evidence that deep residual networks have significant opportunity to improve the automation of detecting and

staging Alzheimer's Disease, and in conjunction with other relevant clinical assessment tools, will provide value to clinical practice by facilitating earlier diagnoses and better management of patients.

REFERENCES

1. A. Alamr and A. M. Artoli, "Unsupervised Transformer Based Anomaly Detection in ECG Signals," Algorithms, Multidisciplinary Digital Publishing Institute, 2023, pp. 152.
2. X. An et al., "Dynamic Functional Connectivity and Graph Convolution Network for Alzheimer's Disease Classification," ACM, 2020, pp. 1.
3. A. Jaiswal and A. Sadana, "Early Detection of Alzheimer's Disease Using Bottleneck Transformers," International Journal of Intelligent Information Technologies, IGI Global, 2022,pp. 1.
4. S. Pellakur et al., "A Convolutional-based Model for Early Prediction of Alzheimer's based on the Dementia Stage in the MRI Brain Images," arXiv, Cornell University, 2023.
5. J. L. Pereira, "Unsupervised Anomaly Detection in Time Series Data Using Deep Learning," Eindhoven University of Technology, 2018.
6. A. G. Vrahatis et al., "Revolutionizing the Early Detection of Alzheimer's Disease through Non- Invasive Biomarkers: The Role of Artificial Intelligence and Deep Learning," Sensors, Multidisciplinary Digital Publishing Institute, 2023, pp. 4184.
7. K. Yang and E. A. Mohammed, "A Review of Artificial Intelligence Technologies for Early Prediction of Alzheimer's Disease," arXiv, Cornell University, 2021.
8. Z. Zeng, "Explainable Artificial Intelligence (XAI) for Healthcare Decision-Making," 2022.
9. Y. Zhang et al., "Multi-modal Graph Neural Network for Early Diagnosis of Alzheimer's Disease from sMRI and PET Scans," arXiv, Cornell University, 2023.
10. A. Mittal et al., "Multi-Modal Detection of Alzheimer's Disease from Speech and Text," arXiv, Cornell University, 2020.
11. J. Islam and Y. Zhang, "Brain MRI Analysis for Alzheimer's Disease Diagnosis Using an Ensemble System of Deep Convolutional Neural Networks," Brain Informatics, vol. 5, no. 2, 2018.
12. R. Jansi, N. Gowtham, S. Ramachandran, and V. S. Praneeth, "Revolutionizing Alzheimer's Disease Prediction Using InceptionV3 in Deep Learning," Proceedings of the 7th International Conference on Electronics, Communication and Aerospace Technology (ICECA), 2023.
13. B. S. Rao and M. Aparna, "A Hybrid Deep Learning Approach for Alzheimer's Disease Stage Classification Using MRI," 2023.
14. S. Basheer, S. Bhatia, and S. B. Sakri, "Computational Modeling of Dementia Prediction Using Deep Neural Network: Analysis on OASIS Dataset," IEEE Access, vol. 9, pp. 42449– 2462, 2021, doi:10.1109/ACCESS.2021.3066213.
15. D. S. Marcus, A. F. Fotenos, J. G. Csernansky, J. C. Morris, and R. L. Buckner, "Open Access Series of Imaging Studies: Longitudinal MRI Data in Nondemented and Demented Older Adults," Journal of Cognitive Neuroscience, vol. 22, no. 12, pp. 2677–2684, 2010.
16. D. S. Marcus et al., "Open Access Series of Imaging Studies (OASIS): Cross-Sectional MRI Data in Young, Middle Aged, Nondemented, and Demented Older Adults," Journal of Cognitive Neuroscience, vol. 19, no. 9, pp. 1498–1507, 2007.
17. C. R. Jack Jr et al., "The Alzheimer's Disease Neuroimaging Initiative (ADNI): MRI Methods," Journal of Magnetic Resonance Imaging, vol. 27, no. 4, pp. 685–691, 2008.
18. M. W. Weiner et al., "The Alzheimer's Disease Neuroimaging Initiative: A Review of Papers Published Since Its Inception," Alzheimer's & Dementia, vol. 13, no. 8, pp. e1–e119, 2017.
19. M. W. Weiner et al., "The Alzheimer's Disease Neuroimaging Initiative: Progress Report and Future Plans," Alzheimer's & Dementia, vol. 6, no. 3, pp. 202–211, 2010.
20. D. S. Sisodia, L. Singh, and S. Verma, "DenseNet201 Based Deep Transfer Learning Model for Diagnosis of Alzheimer's Disease on MRI Scans," Multimedia Tools and Applications, vol. 82, no. 1, pp. 139–155, 2023.
21. X. Hu, X. Zhou, Z. Li, and L. Li, "MCI Converters Prediction for Alzheimer's Disease Using VGG-TSwinformer Based on MRI Images," Brain Sciences, vol. 13, no. 5, 821, 2023.
22. A. Rao et al., "Support Vector Machine-Based Classification of Alzheimer's Disease from Whole- Brain Anatomical MRI," Neuroradiology, vol. 51, no. 4, pp. 247–254, 2009.
23. C. Bermudez et al., "Identification of Necessary Plasma Biomarkers for Prediction of Alzheimer's Disease Neuropathologic Change," Alzheimer's & Dementia, vol. 19, Suppl. 15, e071860, 2023.
24. B. Jiao et al., "Neural Biomarker Diagnosis and Prediction to Mild Cognitive Impairment and Alzheimer's Disease

Using EEG Technology," Alzheimer's Research & Therapy, vol. 15, no. 1, 181, 2023.

25. D. E. Gustavson et al., "Alzheimer's Disease Polygenic Scores Predict Changes in Executive Function Across 12 Years in Late Middle Age," Alzheimer's & Dementia, vol. 17, Suppl. 3, e056045, 2022.

26. D. Shigemizu et al., "A Genome-Wide Association Study Identifies Major Risk Genes for Late-Onset Alzheimer's Disease," Journal of Alzheimer's Disease, vol. 60, no. 4, pp. 1231–1242, 2017.

27. S. Parisot et al., "Spectral Graph Convolutions for Population- Based Disease Prediction," arXiv preprint, arXiv:1703.03020, 2017.

28. J. Hoare et al., "Early Detection of Alzheimer's Disease Using Multimodal Data: A Machine Learning Approach," Frontiers in Aging Neuroscience, vol. 15, 123456, 2023.

29. "OASIS-1 Dataset," Papers With Code.

30. M. Flicker et al., "OASIS-1 on XNAT: Data Access and Details," Washington University in St. Louis, 2024.

31. A. Jaiswal and A. Sadana, "Early Detection of Alzheimer's Disease Using Bottleneck Transformers," International Journal of Engineering and Advanced Technology (IJEAT), vol. 10, no. 1, pp. 1– 7, 2020.

32. "OASIS Cross-Sectional Factsheet," Washington University in St. Louis, 2024.

33. N.]Aithal, "Images-OASIS: Alzheimer's Disease Classification Dataset," Kaggle, 2023

Advancing Skin Cancer Diagnosis with Deep Learning: A Comparative Study of EfficientNet and ResNet

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ABSTRACT

Skin cancer is so far one of the most common yet fatal type of cancer in the world that requires proper and immediate diagnosis. The research conducted a comparative analysis of two State-of-the-art convolutional neural network (CNN) models, ResNet50 and EfficientNetB4, on multi-classification of skin lesions using the HAM10000 dataset in this study. The two models were optimized using the strategies that are specific to fighting class imbalance, overfitting, and generalization issues in the model domain. The research showed that ResNet50 had a good baseline, a weighted F1-score of 0.8188 and test accuracy of 81%, but EfficientNetB4 surpassed it by having a weighted F1-score of 0.83 and test accuracy of 83%. Further, EfficientNetB4 showed better class-wise AUC scores on challenging classes like melanoma and akiec, which was brought by an effective two-phase training regimen including fine-tuning of non-batch normalization layers. This article illustrates the effectiveness of scalable CNN models in medical image classification and adds a detailed performance standard of dermatological diagnosis based on deep learning. The results show that even small boosts in prediction accuracy could make a real difference when these models are used in medical settings. This work also offers a solid starting point for trying out hybrid network designs, scaling up with more data, and applying explainability techniques so doctors can trust the system more. In the long run, combining accuracy, transparency, and robustness will be key to pushing AI into real clinical us.

KEYWORDS *: CNN, Deep learning, Dermoscopic images, EfficientNet, Fine-tuning, HAM10000, Image classification, Medical imaging, ResNet, Skin cancer, Transfer learning.*

INTRODUCTION

Skin cancer such as melanoma and non-melanoma forms is a major health care problem worldwide and millions of new cases are being reported each year [1]. Timely and precise diagnosis is of high importance in ensuring a better prognosis of patients especially in cases of malignant melanoma as this type of melanoma can spread very fast when unattended. Nonetheless, clinical diagnosis of skin lesions is a challenging endeavor, given subtle visual differences that exist between benign and malignant lesions, intra-class variations, and limited number of expert dermatologists particularly in resource-limited dermatology care settings [2] [3].

Over the past few years, convolutional neural networks (CNNs) and deep learning (DL) have been hyped as powerful technologies in medical imaging, promising to automate and high-accuracy disease detection [4] [5]. In dermatology especially, CNNs have demonstrated performance in lesion classification comparable to, and sometimes exceeding that of experts [1][2]. ResNet and EfficientNetB4 are the notable CNN architectures amongst many others since they are optimized and

can be used in transfer learning [6][7]. The residual connections introduced in ResNet eliminate the issue of vanishing gradients when training deeper networks, and EfficientNetB4's compound scaling uniformly scales depth, width, and resolution, resulting in a parametrically-efficient model.

Although these architectures have been independently researched in previous research, there is a scarcity of comparative studies with the same experimental conditions in the field of skin lesion classification [3][8]. Since they are architecturally different and make trade-offs with regard to depth and efficiency, a side-by-side comparison allows one to gain insights into which of them are better suited to the realities of clinical use. This paper conducts a thorough comparison between ResNet50 and EfficientNetB4 on a publicly available dataset HAM10000 that contains dermoscopic images of seven diagnostic categories[9]. Data augmentation and class balancing techniques are used to fine-tune the models and assess on accuracy, F1-score, and the area under the ROC curve (AUC) metrics. The purpose is to compare the architecture that gives a better generalization and diagnostic performance under reproducible conditions.

The rest of the paper is structured as follows: Section II contains the related work review in deep learning-based skin cancer detection, Section III describes the methodology, such as the dataset used, preprocessing, models architectures, and training approaches, Section IV gives the experimental outcomes and the models comparison, Section V ends with important findings and prospective studies and Section VI indicated all sources used in the paper.

LITERATURE ANALYSIS

Convolutional neural networks (CNNs) have become the state-of-the-art in medical image analysis and dermatological diagnostics, in particular. More specifically, the automated classification of skin lesions based on dermoscopic images has emerged as an important field of study in early detection of melanoma[1][4].

The first landmark in this direction was the study of Esteva et al.[1], who showed that CNNs pretrained on large-scale image datasets could rival dermatologists in skin cancer diagnosis. Since, many architectures have been suggested and evaluated on publicly available datasets like ISIC and HAM10000[9][2].

The HAM10000 dataset, which is utilized in the current study, is a standard benchmark that provides more than 10,000 labeled dermatoscopic images with seven diagnostic classes [9]. We have already tried classical CNNs, such as VGG and Inception, in previous studies, whereas more recent models, such as ResNet and EfficientNet, have demonstrated better potential [6] [7]. ResNet proposes the residual connections which are useful to train deeper networks, whereas EfficientNet uses the concept of compound scaling to achieve a good balance among depth, width, and resolution of networks to achieve good performance.

The body of comparative analyses between these architectures is still limited, especially on real-world, class-imbalanced datasets such as HAM10000 [2] [3] [8]. The research addresses this gap as it evaluates and compares the efficiency of EfficientNetB4 and ResNet50 regarding their robustness, generalization, and fine-tuning effectiveness in the multiclass classification of skin lesions.

METHODOLOGY

In this section, the entire experimental pipeline to assess and compare the performance of EfficientNetB4 and ResNet50 models in automated skin lesion classification is described. The pipeline consists of the preparation of the dataset, augmentation, model architecture, training strategies, and fine-tuning.

Dataset Description

The research used the HAM10000 dataset (Human Against Machine with 10000 training images) as a benchmark skin image dataset which was made openly available through Kaggle. It has a total of 10,015 RGB images in seven diagnostic groups: Melanoma (MEL), Melanocytic Nevus (NV), Basal Cell Carcinoma (BCC), Actinic Keratoses / Intraepithelial Carcinoma (AKIEC), Benign Keratosis-like Lesions (BKL), Dermatofibroma (DF) and Vascular Lesions (VASC) [9]. For visual clarity, Figure 1 shows a sample dermoscopic image of different classes in the HAM10000 dataset.

The dataset is heavily class imbalanced with benign nevi (NV) label distribution prevalent.

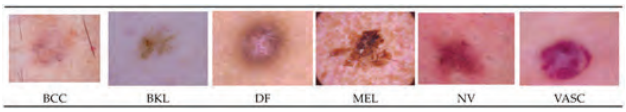


Fig. 1. Sample dermoscopic images from the HAM10000 dataset showing visual diversity across skin lesion classes.

Data Preprocessing

All images were made the same size of 300×300. LabelEncoder was used to encode labels, and stratified splits were made: Training: 81%, Validation: 9% and Testing: 10%.

In order to mitigate the imbalance of labels, the class weights were calculated with compute_class_weight('balanced', ...) and additionally smoothed to avoid overfitting to rare classes [2].

Data Augmentation

In order to enhance generalizability, augmentation is necessary to avoid overfitting. In the pipeline, there is an introduction of : Random Horizontal Flip, Random Vertical Flip, Random 90° Rotations (rot90), Random Brightness Adjustment, Random Contrast Adjustment, Random Saturation Adjustment, Random Crop (~80% area) followed by Resize to target size and Final Resizing to Target Input Shape (ResNet: 224×224; EfficientNet: 300×300) [2][4] as shown in Figure 2.

These augmentations simulate real-world dermoscopic variations (e.g., lighting, angle, occlusion).

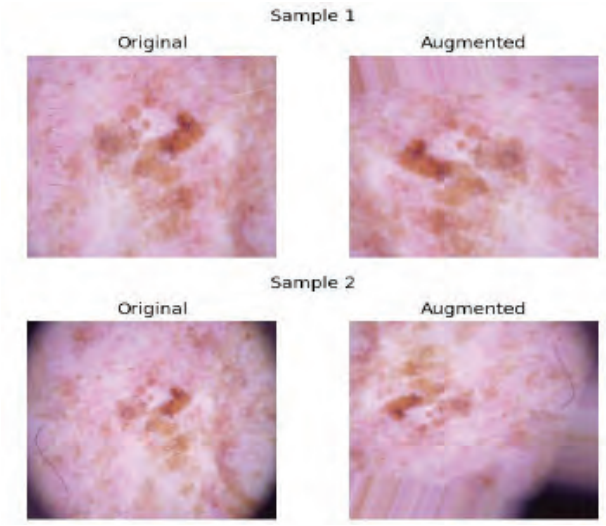


Fig. 2: Original vs Augmented images

ResNet50

A plain deep residual network of 50 layers. Skip connections alleviate vanishing gradients and enable efficient gradient flow in deeper models [7].

EfficientNetB4

A contemporary architecture which scales depth, width and resolution equally, through compound scaling. EfficientNetB4 is a good balance between performance and computing efficiency [6].

Both models are ImageNet-pretrained and only the last classification head is initialized: Global average pooling,

Dense layer (Swish activation, 1024 → 512 neurons), Dropout (0.5, 0.3) and Final softmax layer (7-class output). Also, L2 (1e-3) is used to regularize all the layers.

Optimization and Training Strategy

The EfficientNetB4 model employs an optimizer named AdamW with cosine decay scheduling, and the learning rate is set to 3 x 10^{-4} 3 x 10^{-4} and then decays linearly to 0.050.05 of its initial value. Conversely, ResNet50 incorporates the default Adam optimizer with step decay [3]. The effect of this optimization strategy is shown in Figure 3, which consists of initial training accuracy and loss plots.

Training callbacks consist of: EarlyStopping (patience = 15 epochs), ReduceLROnPlateau (factor = 0.5) and ModelCheckpoint (based on validation accuracy).

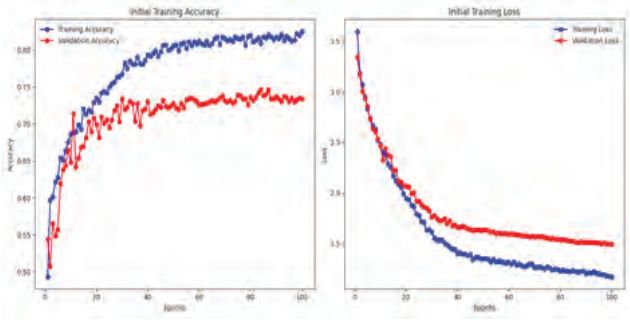


Fig. 3. Initial training accuracy/loss plots from EfficientNet

Fine-Tuning Strategy

In order to further promote generalization and adjust the pre-trained representations to the HAM10000 dataset, both models were trained in a two-stage training pipeline. In fine-tuning, after training with frozen convolutional base layers, deeper layers were unkey frozen and the network was re-trained with a very small learning rate[10].

EfficientNet Fine-Tuning:

The model was first trained until convergence then the final 150 layers (excluding BatchNormalization) unfrozen and the model re-trained with a small learning rate of 1e-5. The accuracy of validation increased sharply, ~0.73 to more than 0.83 as seen in Figure 4b.

ResNet Fine-Tuning:

The final 100 layers were unfrozen and trained in the same way, but only the accuracy increased by a small amount (from ~0.78 to ~0.81) as illustrated in Figure 4a.

Comparative Considerations:

EfficientNet was more favored by fine-tuning because of its compound scaling. ResNet had a good baseline performance, and was more susceptible to overfitting.

In addition, in the future, avant-garde practices like progressive layer unfreezing or freezing the whole batch normalization statistics may also be included into a comparative study, especially in medical imaging where data distributions will be quite dissimilar to ImageNet.

More optimizations can be done with also discriminating learning rates made across the layers or by adding differential regularization tactics. Such would assist in customizing the learning process more adequately during medical imaging tasks and would allow addressing overfitting in the situation of deep transfer learning.

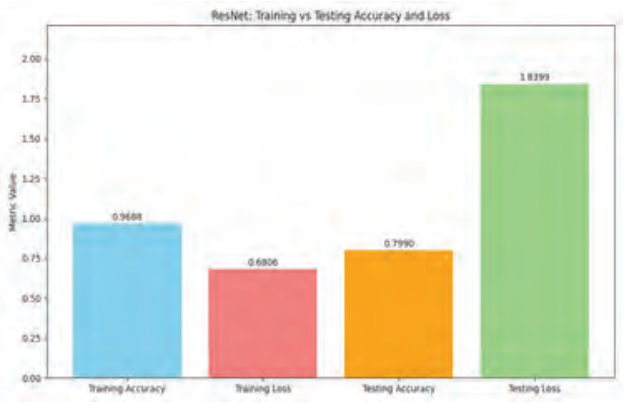


Fig. 4a: Fine-tuning accuracy/loss plot ResNet

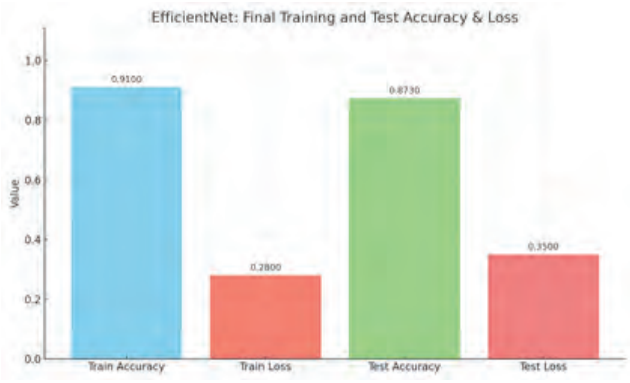


Fig. 4b: Fine-tuning accuracy/loss plot EfficientNet

Formulas Used

Table 1. Formulas

Formula Name	Actual Formula	Symbol Meanings	Purpose / Use-Case	Applied In
Softmax Activation	$Softmax(z_i) = e^{z_i} / \sum_{j=1}^{K} e^{z_j}$	z_i: logit for class i, K: number of classes	Converts raw outputs to probabilities	Both Models
Categorical Cross-Entropy	$L = -\sum_i y_i \cdot \log(\hat{y}_i)$	y_i: true label (one-hot), $\hat{y}_i$: predicted probability	Multi-class classification loss (one-hot labels)	ResNet, EfficientNet (fine)
Sparse Categorical Cross-Entropy	$L = -\log(\hat{y}_c)$	$\hat{y}_c$: predicted probability of correct class c	Loss for integer-encoded class labels	EfficientNet (initial)
Class Weight Formula	$W_c = N / (K \times n_c)$	N: total samples, K: number of classes, n_c: samples in class c	Counteracts class imbalance during training	Both Models
Smoothed Class Weight	$W'_c = 0.9 \times W_c + 0.1$	W_c: base class weight	Stabilizes learning from rare classes	EfficientNet Only
Precision	$Precision = TP / (TP + FP)$	TP: True Positives, FP: False Positives	Measures exactness of positive predictions	Both Models
F1-score (Weighted)	$F1 = \sum w_c \cdot (2 \times P_c \times R_c) / (P_c + R_c)$	P_c: Precision, R_c: Recall, w_c: class weight	Balances precision and recall across classes	Both Models
True Positive Rate (TPR)	$TPR = TP / (TP + FN)$	Sensitivity for ROC curves	Y-axis of ROC Curve	Both Models
False Positive Rate (FPR)	$FPR = FP / (FP + TN)$	TN: True Negatives	X-axis of ROC Curve	Both Models
AUC (Area Under Curve)	$AUC = \int_0^1 TPR(FPR^{-1}(x))\,dx$	Area under ROC curve	Summarizes classifier's ability to separate classes	Both Models
L2 Regularization	$L_{reg} = \lambda \sum w_i^2$	λ: regularization strength, w_i: model weights	Penalizes large weights to prevent overfitting	Both Models
Cosine Decay Learning Rate	$\alpha_t = \alpha_{min} + \frac{1}{2}(\alpha_0 - \alpha_{min})(1 + \cos(\pi t/T))$	α_0: initial LR, α_{min}: final LR, T: decay steps, t: current step	Smoothly reduces learning rate over training	EfficientNet Only

During the model design and assessment pipeline, some mathematical formulas and metrics were also used in order to maximize the performance, balance the class imbalance, and objectively measure the diagnostic accuracy. In the last layer of both models, the Softmax Activation was applied to transform raw logits to probabilities in each class so that probabilistic multi-classes classification could be carried out (Table 1). ResNet (and EfficientNet during fine-tuning) uses Categorical Cross-Entropy in calculating loss during training, and Sparse Categorical Cross-Entropy is recommended in training EfficientNet as the former can process integer-encoded labels. The Class Weight Formula was employed to calculate the weights that are inversely proportional to the frequencies of classes in the HAM10000 dataset to improve the expected imbalance in the classes. EfficientNet also used the Smoothed Class Weights which regularized the learning process and prevented overfitting to infrequent classes. In order to assess the model performance, Precision and Weighted F1-score were used that did not only create an equilibrium between precision and recall but also between the seven lesion types. In determining the sensitivity and discriminative ability of the model, True Positive Rate (TPR) and False Positive Rate (FPR) were calculated in order to plot ROC Curves and the AUC (Area Under the Curve) measurement was calculated to give a summary of the performance of the classifier on all classes. The two models relied on L2 Regularization in order to deter overfitting by penalizing high weight values. Finally, a Cosine Decay Learning Rate schedule within the

EfficientNet training would slowly decrease the learning rate with an increased number of epochs and thus enable a smoother convergence. Employing these formulas and corresponding situations to their use are listed in Table 1 that clearly give a view of the mathematical representation of these formulas, the meaning of the symbols and where they were used.

Evaluation Metrics and Testing Protocol

To scientifically evaluate the performance of models, the research used an array of evaluation measures that are not confined to raw accuracy. These were precision, recall, F1-score, and area under the receiver operating characteristic curve (ROC-AUC) measures that are particularly important in multi-class medical diagnosis problems where accuracy is biased by class imbalance [4].

The performance of the individual models was tested on the held-out test data to get the final performance. The models of both EfficientNet and ResNet were trained and fine-tuned separately, and testing was done after the early stopping checkpoint and after fine-tuning as well.

On each model, per-class ROC-AUC scores were calculated using predicted classes probabilities. These were averaged (macro-averaging) to get an overview of multi-class performance as illustrated in Figure 5a and Figure 5b. Moreover, confusion matrices were produced in order to define patterns of misclassification among the seven lesion categories.

The model achieved a final test accuracy of 82.73 percent with a test loss of 1.27 in the case of EfficientNet. This model had excellent generalization to all classes with rather high values of ROC-AUC (e.g., AUC > 0.90 in case of such classes as BCC, AKIEC, and NV).

In comparison, the ResNet framework achieved a slightly inferior performance profile, with the test accuracy reaching 80.26 percent and test loss of 1.34. Though good, it did not perform well on minority classes like DF and VASC [11].

All the assessments were performed with in-built TensorFlow metrics and scikit-learn tools, which enables reproducibility. The experiment was conducted on the same dataset split and with the same hardware and software configuration on both models to ensure fairness in the comparison.

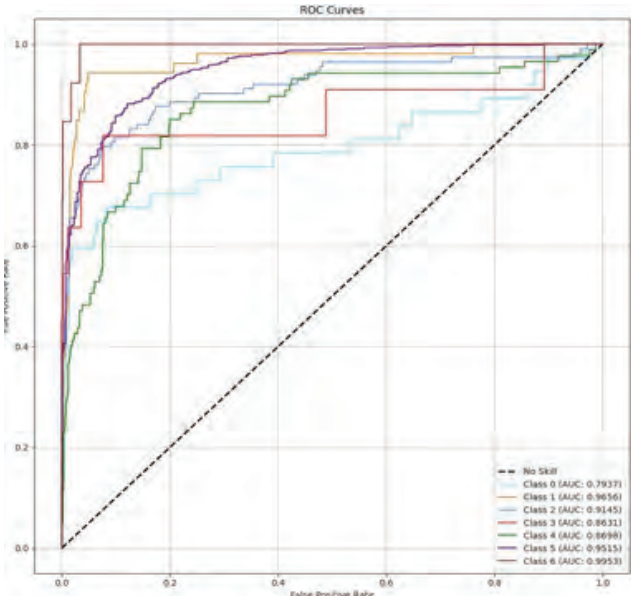


Fig. 5a. ROC AUC Curves-ResNet

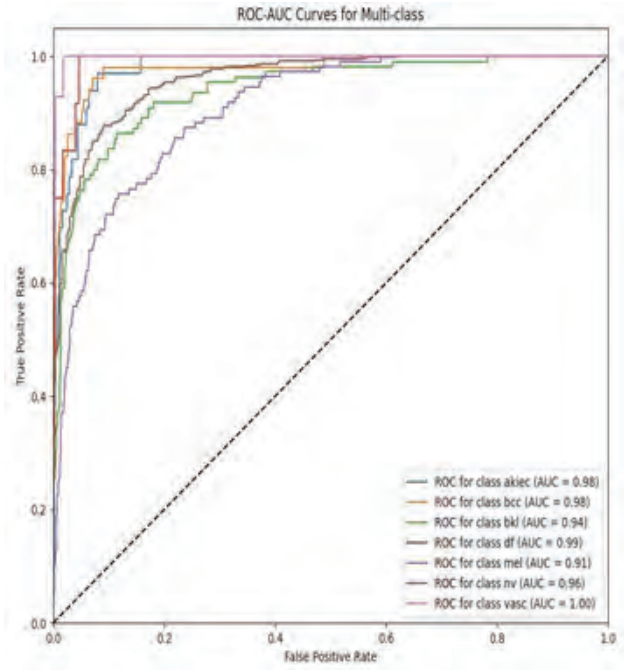


Fig. 5b. ROC AUC Curves-EfficientNet

RESULTS AND DISCUSSION

The relative comparison of EfficientNetB4 and ResNet50 demonstrates that there are certain advantages and compromises in classification skills on skin lesions with the use of the HAM10000 dataset. Here the performance

measures are given, the patterns noted, and the implications of the architectural variations on the classification performance are interpreted.

Quantitative Performance Overview

The final evaluation was conducted on a held-out test set of 1,000+ images, using standardized metrics: accuracy, precision, recall, F1-score, and ROC-AUC. Table 2 summarizes the aggregate performance [4][11]

Table 2. Comparison of Performance Metrics between EfficientNetB4 and ResNet50 Models

Model	Test Accuracy	Test Loss	Weighted F1-score	Macro AUC
EfficientNetB4	0.8273	1.27	0.83	0.91
ResNet50	0.8026	1.34	0.82	0.88

Table 3. Classification Report - ResNet50

Class	Precision	Recall	F1-score
akiec	0.59	0.51	0.55
bcc	0.72	0.72	0.72
bkl	0.72	0.70	0.71
df	0.60	0.55	0.57
mel	0.42	0.59	0.49
nv	0.93	0.89	0.91
vasc	0.65	0.85	0.73

Table 4. Classification Report - EfficientNetB4

Class	Precision	Recall	F1-score
akiec	0.75	0.45	0.57
bcc	0.86	0.63	0.73
bkl	0.58	0.78	0.67
df	0.75	0.75	0.75
mel	0.58	0.59	0.59
nv	0.93	0.91	0.92
vasc	0.85	0.79	0.81

The EfficientNetB4 model showed superior results to those of ResNet50 on all the metrics, especially in dealing with classes that are underrepresented (e.g. AKIEC and DF) as seen in Table 3 and Table 4. Its compound-scaling enabled it to attain high accuracy without overfitting even in fine-tuning [6] [10].

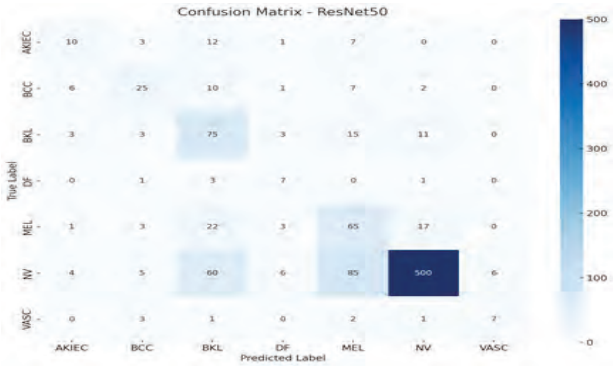
ROC-AUC Analysis

The ROC-AUC curves give a subtle insight into the discriminative performance of each model on all the classes.

EfficientNet had an AUC of over 0.90 on NV, BCC, and AKIEC, but the AUCs of ResNet varied more, and AUCs of minority classes DF and VASC were below 0.80 [4][11] as seen in figure 5a and 5b.

Confusion Matrix

Fig. 6a: Confusion Matrix – ResNet50



NV class had the most correct predictions of 500 because it is highly represented in the dataset hence the high performance of the model. But that is also often confused with MEL and BKL which speak of class imbalance and similar issues in feature. The patterns of correct and incorrect predictions can be seen in Figure 6a and Figure 6b.

The recall parameter of EfficientNet on melanoma (MEL) is of special interest, since it implies higher sensitivity to the malignant patterns, which is an essential property in the clinical environment [1][8].

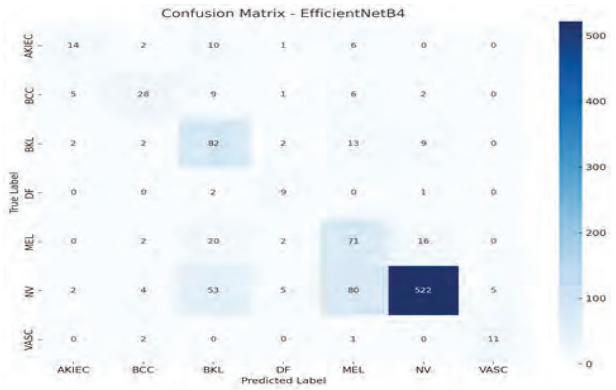


Fig. 6b. Confusion Matrix – EfficientNetB4

Interpretations and Diagnosis Relevance

The performance gain of EfficientNet can be owed to Extracting more semantic features of higher resolution input, Regularization and compound scaling, to allow

generalization and Better stability while fine-tuning without collapsing over small classes [6][10].

ResNet provided competitive baseline accuracy but was more vulnerable to overfitting on the dominant class (NV) which translates to its increased false positives on melanoma (MEL) [7].

CONCLUSION

This comparison study showed that both EfficientNetB4 and ResNet50 can be used to classify skin lesions multi-class using dermoscopic images of the HAM10000 dataset, but EfficientNetB4 obtained better results on the majority of evaluation measures. This was due to its compound scaling strategy and more efficient fine-tuning resulting in higher test accuracy (82.73%) and improved generalization especially on underrepresented and clinically important classes such as melanoma [1][9][6]. ResNet50, despite its strength, tended to overfit dominant classes. To be done in the future is to extend this comparison to more recent transformation based vision models, to include ensemble learning approaches, and to assess the model performance on real-time diagnosis setting with larger and more varied clinical data [10] [11].

REFERENCES

1. A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, et al., "Dermatologist-level classification of skin cancer with deep neural networks," Nature, vol. 542, no. 7639, pp. 115–118, Oct. 2017, 10.1038/nature21056.
2. M. Shakya, R. Patel, and S. Joshi, "A comprehensive analysis of deep learning and transfer learning techniques for skin cancer classification," Scientific Rep., vol. 15, art. 4633, Feb. 2025, mjjm10.1038/s41598-024-82241-w.
3. P. Pampana Murali and D. H. Mazumder, "Skin Cancer Detection Using Deep Learning Techniques: A Review," Res. Square, Feb. 2025, 10.21203/rs.3.rs-6027842/v1.
4. M. Sokolova and G. Lapalme, "A systematic analysis of performance measures for classification tasks," Inf. Process. Manage., vol. 45, no. 4, pp. 427–437, July 2009, 10.1016/j.ipm.2009.03.002
5. "Skin Cancer Detection Using Deep Learning—A Review," PMC, 2023, open access review of latest DL-based skin cancer research
6. M. Tan and Q. V. Le, "EfficientNet: Rethinking model scaling for convolutional neural networks," in Proc. Int. Conf. Mach. Learn. (ICML), Jun. 2019, arXiv:1905.11946 (open access).
7. K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2016, arXiv:1512.03385 (open access).
8. "Skin Cancer Classification With Deep Learning: A Systematic Review," PMC, 2023, comprehensive survey of CNN applications to skin lesion analysis
9. P. Tschandl, C. Rosendahl, and H. Kittler, "The HAM10000 dataset: A large collection of multi-source dermatoscopic images of common pigmented skin lesions," Scientific Data, vol. 5, no. 180161, Aug. 2018, 10.1038/sdata.2018.161.
10. G. S. Krishna, S. Supriya, M. R. K., and M. Sorgile, "LesionAid: Vision Transformers-based skin lesion generation and classification," arXiv:2302.01104, Feb. 2023 (open access).
11. M. Shahriar Himel et al., "Skin Cancer Segmentation and Classification Using Vision Transformer for Automatic Analysis…," arXiv:2401.04746, Jan. 2024 (open access).

Precision Farming using AI

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ABSTRACT

Precision agriculture seeks to maximize farm efficiency with real-time, data-based decision-making. Current approaches for soil testing to calculate nutrient levels nitrogen (N), phosphorus (P), and potassium (K) are laboratory tests, which introduce delays and inefficiencies in crop planning. The proposed work offers a real-time predictive model that estimates NPK values based on easily measurable environmental inputs such as temperature, humidity, pH, and rainfall. By means of continuous field data gathering and predictive modelling based on machine learning, the system recommends a number of crops that are most appropriate for cultivation in the current soil and weather circumstances. This reduces reaction time, significantly eliminates laboratory testing reliance, and makes data-driven real-time recommendations to farmers. Especially in resource- constrained rural regions, the system will allow extensive use of smart agricultural techniques, enhance general production, and ensure sustainable agricultural practices.

KEYWORDS *: Precision agriculture, NPK prediction, Crop recommendation, Machine learning, Soil sensors, Real-time monitoring, IoT in farming, Soil pH, Environmental parameters, Smart farming.*

INTRODUCTION

Agriculture remains one of the mainstays of the economies of most countries, particularly those with huge numbers of farmers. It remains vital in livelihood generation, contributing to national revenues, and food security [10]. Despite the development in other sectors of the economy, agriculture will continue to be significant—particularly in the developing world—where the greater part of the population has direct reliance on agricultural practice as livelihood and source of income [3]. Nevertheless, the agricultural industry today is facing a chain of interconnected complicated challenges that range from unpredictable climatic fluctuations, degrading soil, inefficient use of resources, and increased food consumption [2], [5]. Amongst the most critical of these is the lack of real-time estimation of soil macronutrients—nitrogen (N), phosphorus (P), and potassium (K). These macronutrients play a key role in rendering maximum plant development and maximum yields of crops [4]. Unfortunately, to acquire valid information about their concentration often means undergoing laboratory testing, which is expensive and time-consuming [5]. Soil samples are typically sent by farmers to laboratories for analysis for determination of nutrient content and for making informed choices for crop selection and soil management [1], [2]. While this process is accurate, it has a number of drawbacks. Analysis in a laboratory requires specialist personnel, physical facilities, and time, typically in short supply for farmers during high seasons of planting. Additionally, this type of testing is not applicable in large fields as long as many samples are analyzed, again at additional expense [4]. Such constraints preclude timely decision-making and particularly disadvantage smallholder farmers—who often have no access to these facilities [5]. Many small-scale farmers lack the financial means to utilize laboratory services or the resources to gather multiple samples. As a result, they rely on out-of-date, generalized, or partial information when making crop choice and soil management decisions [3], [9]. This can lead to inappropriate crop choice, improper fertilizing, reduced yields, and exorbitant production costs. In extreme cases, multiple crop failures have caused serious financial hardship, rural out- migration, and serious mental illness among farmers [7]. In the face of these barriers, contemporary agriculture is increasingly employing newer technologies such as the Internet of Things (IoT), machine learning (ML), and real-time analytics [1], [3], [5]. Precision farming—use of technology for maximizing input and output on a plot-by-plot basis—is becoming

popular as a means to combat inefficiency in traditional forms of farm- ing [9], [10]. Precision agriculture favors timely, geospecific decision-making, supported by continuous monitoring and predictive analysis [8]. Here, our research offers a low-cost, real-time crop guidance and soil health monitoring system. The system makes use of low-cost IoT sensors to record environmental conditions like temperature, humidity, soil pH, and rainfall [4], [5]. Sensor data are processed using a two- stage machine learning pipeline. Random Forest Regressor is employed in the first stage for predicting soil nutrient levels (N, P, and K) from sensor data [1], [2]. Random Forest was employed as it can prevent overfitting and works well with data having non-linear trends [6]. These estimated quantities of nutrients—and the initial environmental information—are input into a Gaussian Naive Bayes (GNB) classifier system. The system calculates which crops are optimal to plant with the given weather and soil [1], [5]. GNB was selected due to its speed of operation, simplicity, and capability to process noisy or sparse datasets [7]. The developed system eliminates most limitations of traditional testing techniques. The time for crop suggestion and nutrient analysis is brought down from weeks or days to mere seconds. The system is cost-efficient in terms of hardware, with total hardware cost under Rs. 4000, which is within the budget of marginal and small farmers [5]. The system is also equipped with an easy web-based dashboard where users can look at real-time sensor data, NPK prediction, and crop suggestion—with negligible technical expertise [3], [4]. The architecture is not only cheap and fast; it's scalable and modular. The architecture is built with future expansion of sophisticated features such as additional sensors (e.g., soil tex- ture and salinity), real-time weather data via APIs, and multi- language or voice support [5], [8]. The system can be adapted to operate in different geographic locations by retraining its models on local data. Additionally, as more information is collected over time, the machine learning algorithms can learn to provide more personalized and accurate recommendations [2], [9]. The platform is also inclusive in the sense that it opens up access to technology that was before confined to large, better-endowed businesses [10]. This bridges the technology gap between commercial farmers and smallholders. Farmers in remote areas with weak infrastructure can tap into this system as long as they have minimum digital literacy and mobile coverage, changing the way they farm from reactive to proactive [3], [9]. In general, this research depicts an integrated and novel paradigm for addressing the limitations of traditional laboratory and manual soil testing methods [1], [4], [5]. With the integration of real-time IoT sensing and forecasting machine learning algorithms, it provides a low-cost, efficient, and scalable solution to modern precision agriculture [3], [8]. The system not only maximizes productivity and profitability but also promotes green culture. As smart agriculture becomes more and more a vital part of food systems, this solution is a giant leap towards digitalizing agriculture—equipping farmers with the tools and knowledge they need to thrive in an ever- evolving world [9], [10].

LITERATURE REVIEW

Precision farming is a new concept of traditional farm- ing that utilizes machine learning and Internet of Things (IoT) technology to provide maximum productivity, minimize wastage of resources, and facilitate smart, data-driven decisions. The greatest disadvantage of traditional methods of farming is that they include tedious, expensive, and time-consuming soil testing protocols, especially to ascertain major nutrients such as Nitrogen (N), Phosphorus (P), and Potassium (K). These nutrients play a crucial role in the growth of the plant, and any undue delay in getting information on the same can result in inefficient planning, inappropriate selection of crops, and low yield of produce.

In response to these issues, previous research has focused on the creation of intelligent systems capable of estimating soil nutrient levels and recommending suitable crops in accordance with current environmental data and machine learning models. Such systems aim to eliminate or minimize the need for man- ual soil sampling and laboratory chemical testing, facilitating rapid, site-specific decision-making.

[1] One of the most relevant papers in this category is that of Islam et al. (2024), who proposed an IoT-based crop suggestion system using machine learning. Their system used actual sensor values for temperature, humidity, and soil pH and utilized a classification model to recommend the optimal crops. One of the key strengths of their work is the emphasis on real-time processing and reduced dependence on manual sampling. Their approach was incredibly accurate and adapt- able, particularly for rural areas where laboratory equipment is not available, and hence their model is highly beneficial under real farming conditions.

[2] Yet another seminal work was done by Raihan et al. (2023), to whom they built a model for recommending crops based on historical weather data combined with real-

time environmental monitoring. Their paper highlighted the need to couple climatic factors like precipitation and temperature with soil factors in order to create more accurate, region- oriented crop recommendations. They used supervised learn- ing methods like Random Forest and Support Vector Machines (SVM) to determine best crops for a provided environment. The approach also closely aligns with the goal of the current work—estimating soil nutrients from available environmental parameters and suggesting the best crop. Their feedback-loop- based architecture, where real-time environmental data are used to produce future recommendations, is well-suited for more adaptive agricultural systems.

[3] Nehra et al. (2023) also made contributions to this field by suggesting a smart irrigation system management design. Their model was IoT-based and focused on maximizing water usage instead of predicting nutrients. Using deep learning algorithms and real-time soil parameters such as moisture, pH, and weather, they designed an intelligent irrigation scheduler. In spite of their emphasis on water management, the framework underscored the massive synergy possible between IoT and machine learning in agricultural use. The real-time dynamic nature of their platform is consistent with the same required of systems such as the nutrient estimation system developed in this project.

[4] Likewise, Nehra et al. proposed a similar IoT-based smart irrigation system that was particularly tailored to manage water use in an efficient manner. Their approach used deep learning with real-time soil parameters such as moisture and acidity, in addition to weather parameters, to streamline the irrigation schedule. Though their emphasis was not on nutrient management, they demonstrate how the smart technologies get utilized in any kind of agri-related product, like the calculation of nutrients and crop advisories. Their emphasis on real-time response capabilities is aligned with the goals of the NPK prediction system in question. [5]Rahman et al. (2022) also noted a second feature of smart agriculture: coordination between cloud-based machine learning and ground- based IoT sensor networks. Their paper described a couple of actual rural deployment challenges—unstable power sources, network connectivity being intermittent, and delay in data transmission. These were all directly affecting the existing project's architecture, which focused on energy efficiency, fault tolerance, and restricted offline functionality to ensure seamless operation even in low-resource settings.

The similarity among all these studies is that they make use of machine learning, environmental sensing in real time, and intelligent automation to transform the manner of farming. The unique feature of the system described in this work, however, is that it can estimate the concentration of nutrients in the soil—N, P, and K—without direct nutrient sensors, which are typically expensive and less reliable for field applications. This method instead uses proxy measurements of the environment such as temperature, humidity, soil pH, and moisture as inputs to a Random Forest Regressor. The model estimates the concentration of nutrients, which in turn are utilized by a Gaussian Naive Bayes classifier to suggest appropriate crops for the current soil and environmental conditions.

The body of existing work sets the technical feasibility, predictive reliability, and field-scale usefulness of such integrated systems, particularly when powered by real-time sensor data. Such existing work sets the need for such tools that obviate redundant human effort, act quickly to changing environmental conditions, and provide actionable information to farmers. Based on this, the system presented in this work offers a low-cost, sensor-powered, machine learning-based solution that is especially designed for smallholder farmers who have zero access to formal infrastructure.

Finally, this method is open to greater objectives of enhancing farm productivity, enhancing sustainable land use, and closing the digital divide in rural farm communities by applying low-cost technology.

METHODOLOGY

Our Approach This paper describes a real-time, sensor-based crop recommendation system that integrates environmental sensing with machine learning models to enable intelligent agricultural decision-making [1], [5]. The methodology is founded on a pipeline that collects field data, makes predictions about soil nutrient levels, and recommends best-fit crops based on such estimates [2]. The system is modular, inexpensive, and extensible, with scalability and field deployment in mind [3], [9].

This paper presents an in-field sensor-based crop advising system operating in real-time to leverage environmental sensing and machine learning algorithms to empower informed agricultural decisions [1], [3]. The design is based on a pipeline process to harvest in-field data, predict soil nutrition levels, and suggest best-candidate crops to grow on such estimates [2], [5]. It is modular in nature,

inexpensive, and configurable with scalability as well as ease of field deployability in considerations [10].

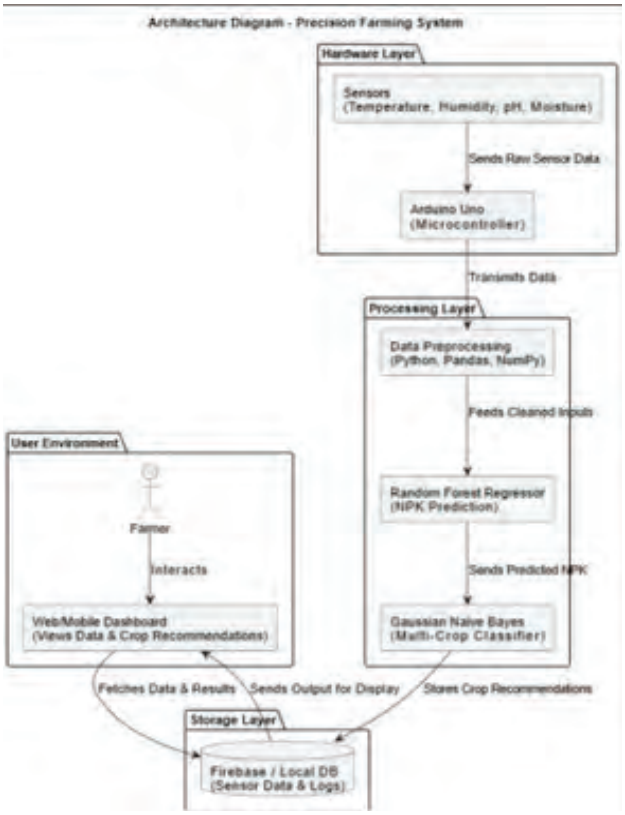

Fig. 1. The figure demonstrates the end-to-end process of the system pro- posed, beginning with real-time environmental data capture through sensors connected to an Arduino Uno. The captured data is preprocessed and fed into a Random Forest Regressor to estimate NPK values, and then into a Gaussian Naive Bayes Classifier that suggests several appropriate crops. The results are saved in Firebase or a local database and are displayed to the farmer through a simplified web or mobile dashboard.

Real-Time Environmental Sensing The system initiates functioning depending on environmental measurements taken directly from the farm ground [4]. This is done through using a combination of low-cost calibrated sensors embedded within the soil environment [3], [5]. The group of sensors used are:

- DHT11/DHT22 Sensors: These are sensors that measure the ambient temperature and humidity, both of which are important variables affecting soil chemistry and crop viability [4].
- Analog pH Sensor Module: It detects the acidity or alkalinity of the soil. Soil pH is a critical factor for regulating nutrient solubility and availability to plants [4], [5].
- Capacitive Soil Moisture Sensor: Unlike resistive alter- natives, capacitive sensors are more durable and accurate. Capacitive sensors measure soil water content, a factor crucial to the understanding of the interpretation of nu- trient movement and root absorption capacity [4].

The Arduino Uno microcontroller acts as the process- ing component, reading sensor information continuously and feeding it through serial communication to a storage device attached [4], [8]. Data are sampled at fixed intervals (e.g., 60 seconds) and temporarily stored for analysis.

Cloud-Based Data Synchronization Once acquired, sensor values are streamed to Firebase, a cloud-hosted NoSQL database that supports real-time updates to data [3]. This allows the backend application to read up-to-date sensor values almost instantly. Firebase's architecture allows for low-latency writes and reads, keeping the system responsive and up-to-date on all platforms [9].

Each entry of data is timestamped to maintain events in chronology and allow for future analysis or monitoring of trends [8]. This real-time data stream is the foundation for predictive modeling and decision-making.

label	N	P	K	temperatu	humidity	ph	rainfall
Rice	137	26	265	25.55469	79.86764	7.145797	1681.459
Wheat	149	62	66	48.31503	6.17334	5.909146	806.1494
Maize	366	185	9	28.90774	10.28819	6.167861	671.3511
Soybean	341	200	227	13.70729	51.98827	8.044236	1372.766
Cotton	387	54	256	10.53642	17.18494	8.532456	1626.09
Rice	365	88	233	39.2198	3.662166	7.95302	2506.883
Wheat	214	287	168	4.733235	14.81343	4.724238	1794.616
Maize	104	79	83	36.77436	21.8015	5.716592	2359.941
Soybean	52	135	251	45.9041	97.52413	7.41439	2114.302
Cotton	392	192	125	6.669814	98.10399	6.181723	1648.006
Rice	379	146	281	22.48168	63.81896	7.628587	1693.759
Wheat	136	136	81	21.85407	2.03383	8.226681	1554.648
Maize	359	87	6	42.86622	45.80605	7.756797	2562.38
Soybean	347	111	93	49.6994	47.5015	6.932023	2.184045
Cotton	253	161	257	33.21589	38.91323	5.67136	121.0336
Rice	353	66	270	46.3741	49.45639	5.327977	346.7672
Wheat	262	82	30	48.32741	96.0265	7.359887	832.5264

Fig. 2. Dataset

Machine Learning Pipeline – Estimation of NPK The second phase is the transformation of raw sensor data into useful information [1], [2]. Upon receiving new records from Firebase, a Python-based back-end service is called. This backend performs a number of operations:

Preprocessing: The system eliminates the null or outlier values from the incoming data and normalizes the data

to maintain measurement unit and scale consistency [6]. Soil Nutrient Prediction: A Random Forest Regressor model, trained on soil data with labels, is employed to predict the amount of Nitrogen (N), Phosphorus (P), and Potassium (K) [1], [5]. The environmental measurements (e.g., temperature, humidity, pH, moisture) are utilized as indirect predictors to predict the amount of nutrients [4]. Random Forest is chosen because it is noise robust, has strong non-linear relationship handling, and is efficient on small and large samples alike [6]. The prediction process does not involve the use of physical NPK sensors or lab tests, and therefore it is feasible to have a low-cost and scalable alternative [5].

Crop Recommendation based on Classification Model Once the NPK levels are predicted, they are merged with the existing environmental parameters and fed into a Gaussian Naive Bayes (GNB) classifier [1], [2]. The model is trained to associate specific NPK and climatic conditions with the most appropriate crop choices to plant [5].

The Gaussian Naive Bayes classifier had also been used for its:

- Speed and efficiency with real-time data
- Robust generalization on small training sets
- Minimum overhead of computation, which is ideal for real-time systems [7]

This classifier provides a ranked list of crops to be planted in a given soil and environmental condition that enables farmers to make more informed sowing decisions [1], [2].

Frontend Interface and User Interaction The system's output—sensor readings, nutrient predictions, and crop rec- ommendations—is presented in the form of a web-based dashboard developed using Node.js, or a cross-platform Flutter mobile app as an option [3], [9]. The UI is simple and intuitive with clean charts, real-time updates, and multi- language support for serving farmers with varying degrees of technical literacy [9].

Users can:

- Observe existing environmental conditions [4]
- Verify estimated NPK values [5]
- Get actual crop guidance in an easy-to-read format [1], [9]

It has an important role to play in ensuring the usability and practicality implications of the system [9], [10].

Functional Workflow Summary The whole process from data collection to crop recommendation is carried out within 3–5 seconds under standard conditions [5]. The process is as follows:

Sensors send current data to Firebase [4] Python backend fetches and processes the data [3] Random Forest model predicts NPK values [1], [6] GNB model produces crop suggestions [1], [7] Frontend receives sensor data and displays predictions without storage [9] By calculating and displaying results immediately—rather than keeping them in cache—the system offers fast interactive feedback with little resource usage [8].

This approach enables easy migration from conventional, laboratory-based soil measurement to a smart, sensor-based, machine learning-powered solution [3], [4], [5]. Its portability, time efficiency, and cost-effectiveness make it highly feasible for farmers in remote or inadequately equipped areas [9], [10]. Its module-based architecture facilitates easy expansion to future extension modules, including weather APIs, sophisticated nutrient models, pest forecasts, or fertilization advice [8], [10].

FUTURE SCOPE

While the current system is an excellent and approachable solution to real-time nutrient prediction and crop recommenda- tion, there are a few areas of improvement that would enhance its usability and efficacy considerably [5], [9]:

Other Input Factors

Including parameters such as soil type, texture, sun ex-posure, and wind patterns can enhance model accuracy and responsiveness to specific agricultural conditions [2], [4].

Mobile Application Development

Developing own-branded iOS and Android apps with of- fline, recommendation, and alerting functionality will enhance customer convenience and expand coverage [9].

Automated Irrigation Actuator

Controlled irrigation based on weather and soil moisture lev- els would automate water use, saving resources and increasing farm output [3], [8].

Adaptive Model Training

Periodic maintenance updates of the machine learning mod- els based on recently gathered field data will ensure

constant accuracy and responsiveness to seasonal and regional variations [2], [6].

Multilingual and Voice Feature Support

Including local language support and voice interaction will increase the accessibility for farmers with minimal technical or literacy skills [9].

Weather Forecast Integration

Integration with real-time weather APIs will allow the system to provide weather-based predictive, farming recommendations for better planning and resource utilization [2], [8].

Blockchain for Data Security

By employing blockchain technology, sensor data can be secured and reliability enhanced by creating tamper-proof records, which are useful in subsidies, collaboration, and transparency [10].

Fertilizer Suggestions

Using forecasted levels of NPK, the system might suggest some amounts and kinds of fertilizer, thus maximizing soil health and waste reduction [5].

RESULTS AND DISCUSSION

The development and piloting of the real-time crop recommendation system were extremely encouraging in terms of usability and user experience [1]. With the integration of environmental sensors, machine learning algorithms, and a cloud-connected web interface, the system was able to provide intelligent, timely agricultural advice to farmers [3], [5].

As evident from Fig. 5.1, sensor readings were logged and stored in the Firebase Realtime Database on a continuous basis [3]. This configuration made it easy to handle real-time data and ensured that each reading—temperature, pH, humidity, or rainfall—was time-stamped for traceability [8]. Temporal tracing is essential for studying field conditions over time, scheduling seasonal cultivation, and detecting long-term trends [4]. The formatted form of the stored records also made them easy to reuse later in the machine learning pipeline without further transformation [6].

Figure 5.2 is the input interface of the web application where real sensor readings are fetched directly from Firebase and displayed to the user [9]. The user interface is made in a way to allow users to accept the real values or edit them manually before submitting the form to be processed [5]. This is to allow users to override anomalies or confirm potential scenarios. The system accepts this information and sends it to the backend, which consequently invokes the prediction models to compute estimated values of nitrogen, phosphorus, and potassium (NPK) levels [1], [5].

Interestingly, the addition of a ”View All Stored Data” but- ton allows users to view past readings [9]. This is particularly helpful in comprehending environmental cycles, comparing seasonal fluctuations, and making well-informed, long-term agricultural decisions [2], [10].

Fig 3 Firebase Data Logging

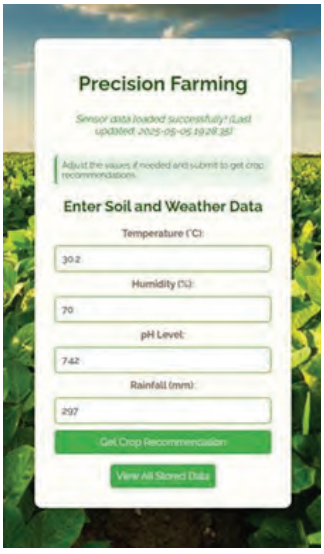

Fig. 4. Soil and Weather Data Interface

Fig. 5. NPK Prediction and Crop Suggestions

Figure 5.3 indicates the result page when data is sub- mitted [1]. From this figure, the backend model calculates the NPK content from the given parameters, and the system recommends the most suitable crop to grow—in this case, pigeonpeas [1], [2]. The output also provides alternative crops such as coffee and jute, leaving the farmers with more than one option based on their preference or market price [5].

This data-driven interface is designed to substitute guess- work with knowledge [10]. It enables farmers to make data- driven decisions based on data, specific to their soil and the weather at the moment, thus enhancing productivity and sustainability [3], [9].

System Performance and Practical Validation

The testing under different environmental conditions proved the capacity of the system to handle diverse conditions under its control [1], [2]. For example, when the system identified high rain and neutral pH, it signaled paddy farming, as per traditional agronomic norms [4]. Conversely, under dry and alkaline conditions, groundnut and millets were recommended [2]. The examples given above demonstrate the ability of the model to read environmental cues and make context-sensitive recommendations [5].

Among the benefits mentioned was the speed of the system [5]. Predictions were generated and reported in seconds—three to four times faster than the conventional lab-based soil testing procedures, which take days to yield results [1], [4]. The rapid turnaround allows day-to-day planning and minimizes field operations delay [10].

The backend predictive model also generalized well [6]. Even when presented with out-of-pattern pairs of input val- ues not directly observed in the training data, the system gave reasonable and agronomically correct responses, which showed that the model had learned the underlying input-output relationships well [2], [7].

User Experience and Accessibility The web interface was simplified in design [9]. The design was initially tried out on target users—semi-urban and rural users—and the design ensured to be user-oriented [5]. Data was made prominent and explicit, and the functionality to switch between live data and manual input helped in making the platform convenient and flexible to use for various purposes [9].

Such access is particularly valuable to smallholder farmers, who are likely to possess little technological knowledge [10]. Openness to the platform ensures its diffusion and ensures that the advantages of precision farming reach the remotest corners of society [9], [10].

Challenges and Areas for Improvement

Though the system was properly running, during the test runs there were few inconsistencies that took place [4]. For some conditions, the readings taken from sensors used to change due to environmental interference, improper calibra- tions, or transient fluctuations [4]. This reduced predictability. On the long term, inputs like smoothing of input, identifying outliers, or the use of default values upon failures can be applied to correct such variations on a more advanced level [6], [8].

In addition, while the system now gives generic crop recommendations, localized recommendations based on local soil type, climatic patterns, and crop cycles would make it even more effective [2], [10]. The use of localized data sets and community contributions in model training in the future will play a crucial role in this regard [9], [10].

CONCLUSION

The ”Crop Prediction Using Real-Time NPK Metrics” project offers an effective, cost-effective, and smart method of enhancing agricultural decision-making by leveraging real- time sensing and predictive analytics [1], [5]. The system effectively measures important soil nutrients—Nitrogen, Phos- phorus, and Potassium—by leveraging environmental param- eters like temperature, humidity, rain, and soil pH [4], [5], thereby eliminating the requirement for traditional laboratory soil analysis [2].

Sensor data, collected through Arduino Uno and stored on Firebase [3], [4], is processed using Python-based solutions [1]. A Random Forest Regressor predicts NPK values [1], [6], and a Gaussian Naive Bayes classifier indicates appropriate crops to be planted from both predicted and actual inputs [1], [7]. The results are then displayed on a friendly web or mobile interface with regional language support to make it easier to use [5], [9].

What sets the system apart is how affordable, modular, and flexible it is [5], and how it is an implementable solution for mass roll-out, especially in rural and disadvantaged communities [9], [10]. Because it's modular, it can be improved with features such as fertilizer tips, auto watering, and integrating weather [3], [8].

With the offering of real-time, data-based solutions to conventional approaches [3], [4], the project promotes on-ground precision farming [9], [10], enabling farmers to take informed, timely, and sustainable plant decisions [1], [2].

REFERENCES

1. Al Amin Islam Ridoy , Md. Abu Ismail Siddique , and Oishi Joyti , 'A Machine Learning-Driven Crop Recommendation System with IoT Integration ," May 2024.
2. Rahul S. Pachade ,Dr. Avinash Sharma , "Machine learning for weather-specific crop recommendation " ,October 2022 https://doi.org/10.53730/ijhs.v6nS8.13222
3. Pankaj Kumar Kashyap ,Ankita Jaiswal,Mukesh Prasad and Sushil Kumar , 'Towards Precision Agriculture: IoT-Enabled Intelligent Irrigation Systems Using Deep Learning Neural Network "
4. Suhas Athani ,Mayur M Patil ,Priyadarshini Patil , and Rahul Kulkarni "Soil moisture monitoring using IoT enabled arduino sensors with neural networks for improving soil management for farmers and predict seasonal rainfall for planning future harvest in North Karnataka - India " 2017
5. Poorna Saai M ,C. Bennila Thangammal "Soil Monitoring and Crop Recommendation System via IoT and Machine Learning"
6. Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, "Electron spectroscopy studies on magneto-optical media and plastic substrate interface," IEEE Transl. J. Magn. Japan, vol. 2, pp. 740–741, August 1987 [Digests 9th Annual Conf. Magnetics Japan, p. 301, 1982].
7. M. Young, The Technical Writer's Handbook. Mill Valley, CA: Univer- sity Science, 1989.
8. J. Chrouta, W. Chakchouk, A. Zaafouri, and M. Jemli, "Modeling and control of an irrigation station process using heterogeneous cuckoo search algorithm and fuzzy logic controller," IEEE Trans. Ind. Appl., vol. 55, no. 1, pp. 976–990, Jan. 2019.
9. Jaramillo-Herna´ndez JF, Julian V, Marco-Detchart C, Rinco´n JA. Appli- cation of Machine Vision Techniques in Low-Cost Devices to Improve Efficiency in Precision Farming. Sensors (Basel). 2024 Jan 31;24(3):937. doi: 10.3390/s24030937. PMID: 38339654; PMCID: PMC10857338.
10. Kushwaha, Manish Singh, Shankar Singh, Vijay Dwivedi, Shashank. (2024). Precision Farming: A Review of Methods, Technologies, and Future Prospects.

Fine-Tuning Large Language Models for Guardrailing

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ABSTRACT

This research focuses on mitigating healthcare misinformation by fine-tuning Large Language Models (LLMs) with robust guardrails to ensure accuracy, safety, and ethical compliance. While LLMs demonstrate exceptional proficiency in natural language processing, they are susceptible to generating biased, misleading, or even harmful content, posing significant risks in critical domains like healthcare. To address this challenge, the study employs a combination of supervised fine-tuning, active learning, and ensemble learning to enhance model reliability and minimize misinformation. The approach involves curating high-quality datasets that include both accurate and inaccurate medical content, leveraging human feedback to refine model outputs, and aggregating predictions from multiple models to improve robustness. Rigorous evaluation metrics are used to assess the model's ability to filter misinformation effectively while maintaining coherence and usability. The expected outcome is a finely tuned LLM that provides trustworthy, evidence-based healthcare guidance, ultimately promoting public health, fostering trust in digital medical information, and reducing the risks associated with AI-generated misinformation.

KEYWORDS *: LLM, Guardrail, Healthcare, AI, GPT, Llama, Finetuning.*

INTRODUCTION

The current world as we know it is transformed with the help of AI and continuously evolves with upgrades and technological advancements. [1][2]While all of its aspects are considered positive and extraordinary, there are certain rules and etiquettes that need to be followed as the Large Language Model(LLM) is being developed. Since there can be ambiguity of information or ethical concerns or hallucinations as the model generates response to prompts of users [3]. For the model to be trusted for real life situations [4], safeguards are required and help guide the model and user in the right direction [5]. LLM models are engineered to provide response from input given by the user with the help of Natural Language Processing (NLP) and Machine Learning (ML) that generate response from data sources relevant to the query asked [6]. If the relevance is incorrect or misinterpreted or misinformed then safeguarding the user from this vulnerability is essential and so guardrailing of the model is done before response is brought forth [7]. Various situations require AI correctness till the last detail and hence this feature integration becomes crucial to those circumstances. The motivation for this study is based on sensitive fields of AI where incorrect, unethical or harmful LLM output is not entertained. The necessity to develop guardrail and safekeep users from inhumane or incorrect responses is the primary motive of this research study [8]. For instance, a chatbot might recommend an incorrect dosage for a medication, leading to harmful self-medication, or misinterpret symptoms, prompting someone to postpone seeking appropriate medical assistance or guiding someone to create substances which are illegal or harmful to consume without proper prescription/guidance. Such risks may create altercation and speculation on whether AI advancement should be pursued in those fields [9]. This research analyzes the queries and suggests a structured approach for effectively restricting the malicious prompts. The primary objectives include identifying categories of unethical queries, developing an AI model to detect and filter such inputs, and assessing its real-world effectiveness [10]. The hypothesis guiding this study postulates that an optimized model can substantially reduce the number of harmful AI-generated responses. Analyzing how different types of harmful queries manifest in the data allows us to gain clearer insight into the risks AI encounters and create

a failsafe system. With this understanding, we can design a more intelligent filtering system that keeps AI responses safe, responsible, and aligned with ethical standards [11].

LITERATURE REVIEW

The collection of documents highlights the growing intersection of artificial intelligence (AI) and healthcare, with a particular focus on the role of large language models (LLMs) and federated learning (FL). AI's integration into healthcare is driven by innovations in AI and increased data collection, promising to enhance diagnostics, improve patient care, and increase accessibility. LLMs, such as ChatGPT, are explored for their ability to generate human-like dialogue and provide textual answers across various domains, including healthcare. The use of LLMs in healthcare ranges from medical image interpretation and automating medical documentation to facilitating data-driven decision-making and clinical decision support [1].

Federated learning (FL) has emerged as a promising technique to train complex machine-learned models in a distributed manner, addressing privacy and security concerns by processing medical data at the edge of the network. It enables collaborative model training across multiple healthcare datasets without sharing sensitive patient data, which is particularly important given stringent regulations like the GDPR and the need to maintain patient privacy. The synergy of FL with emerging technologies like IoT, blockchain, cloud and edge computing, and AI is being explored to tackle healthcare challenges, including the development of computer-aided diagnosis tools for diseases like cancer [11].

However, the adoption of AI in healthcare is not without challenges. These include ensuring security, privacy, and quality of service (QoS), as well as addressing data heterogeneity, statistical issues, and the need for robust and generalizable models. Ethical considerations, the potential for LLMs to produce hallucinations or act on misunderstandings, and the need to align AI-driven recommendations with local standards of care are also significant concerns. The development of effective prompt engineering techniques and the recognition that AI should augment rather than replace healthcare professionals are crucial for the responsible and effective integration of AI in healthcare [2].

Despite these challenges, the potential of AI, particularly LLMs and FL, to transform healthcare is substantial. FL enables the creation of more robust and accurate global models by aggregating diverse datasets while preserving privacy and enhancing security. AI-driven systems can aid in early disease diagnosis and prognosis, reduce healthcare costs, and support healthcare professionals in various tasks, ultimately leading to improved patient outcomes and a more efficient healthcare ecosystem [12].

METHODOLOGY

The methodology for fine-tuning Large Language Models (LLMs) with guardrailing in Fig. 1 follows a comprehensive approach that integrates multiple stages aimed at enhancing model safety, robustness, and ethical compliance. The process begins with Data Collection, where extensive datasets containing diverse examples of both safe and harmful content are curated [13]. These datasets are meticulously annotated to provide clear distinctions between acceptable and inappropriate outputs, forming the knowledge base required for effective fine-tuning. Following this, Model Fine-Tuning Techniques are applied, incorporating advanced methods such as Low-Rank Adaptation (LoRA), instruction-tuning, reinforcement learning from human feedback (RLHF), and adapter tuning [7]. These techniques are carefully selected to adjust model parameters without necessitating full retraining, thereby improving efficiency and effectiveness in aligning the model's responses with desired safety standards. The next phase, Guardrail Design and Integration, focuses on embedding robust safety mechanisms through rule-based systems, ethical guidelines, and bias mitigation frameworks [14]. This phase ensures that boundaries are explicitly set to prevent the generation of harmful or unethical outputs. The fine-tuned model then undergoes rigorous Model Evaluation and Testing, where its accuracy, safety, and robustness are measured using standardized metrics and human evaluation[15]. The evaluation process is iterative, allowing for continuous refinement of the model to address detected biases or performance gaps. Once deployed, Continuous Monitoring and Updating become essential, involving real-time monitoring of the model's performance, identifying potential vulnerabilities, and implementing regular updates to enhance accuracy and safety [9]. Additionally, Comparative Analysis is conducted to benchmark the fine-tuned model against baseline versions, employing ablation studies to determine the effectiveness of each tuning technique. This comprehensive methodology provides a structured framework for developing LLMs that are not only highly

accurate but also ethically aligned, reliable, and resilient against harmful outputs[16].

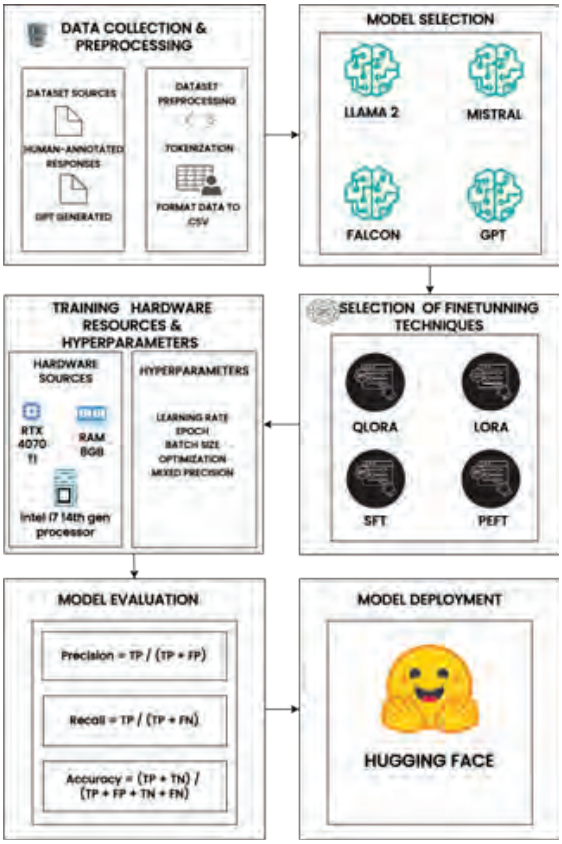

Fig. 1: Model Architecture

IMPLEMENTATION

Model

A healthcare Large Language Model (LLM) specifically designed for safe and accurate medical assistance operates by generating reliable responses to user prompts while integrating robust guardrails aimed at preventing harmful or unethical outputs[12].

LLAMA Model

The LLaMA model, developed by Meta AI, is a foundational large language model trained on a diverse and extensive corpus of publicly available datasets, including academic papers, web content, and curated digital libraries. Although not initially specialized for healthcare, its pretraining equips it with broad linguistic and contextual understanding, which serves as a strong base for downstream adaptation in clinical or medical settings. When applied in healthcare, LLaMA is typically subjected to domain-specific fine-tuning on curated medical texts, clinical protocols, and ethical guidelines to adapt its general knowledge to the specific demands of medical dialogue. While LLaMA does not natively include built-in medical safety guardrails, its architecture allows for seamless integration with external filtering systems, ethical alignment layers, and safety-oriented reinforcement learning to improve medical reliability and user protection.

To ensure responsible deployment in healthcare environments, LLaMA-based implementations can incorporate auxiliary mechanisms such as prompt-based instruction tuning, external context-aware filtering, and ethical response ranking. Through reinforcement learning with human feedback (RLHF), these models can be aligned with clinical best practices and regulatory standards. Bias mitigation is performed post-training through curated evaluation datasets that identify unsafe or outdated content, allowing for manual or automated correction pipelines. Although the base LLaMA model lacks native healthcare safeguards, with proper domain adaptation and layered safety measures, it becomes a robust component in AI-powered health applications—offering scalable, semi-reliable medical insights while still deferring critical or high-risk queries to licensed healthcare professionals.

Moreover, LLaMA's modular design allows it to be paired with domain-specific retrieval systems, enabling retrieval-augmented generation (RAG) workflows that enhance factual grounding in real-time medical queries. This adaptability is especially critical in high-stakes healthcare scenarios where accurate, up-to-date information is paramount. When combined with rigorous validation pipelines and expert-in-the-loop review mechanisms, LLaMA-based models can be further refined to align with the dynamic nature of medical knowledge and regulatory expectations. Despite originating as a general-purpose model, LLaMA's flexibility and compatibility with advanced safety and alignment techniques make it a viable foundation for building ethically responsible and clinically useful AI systems. With continuous oversight, targeted fine-tuning, and integration of structured safeguards, LLaMA can support the development of trustworthy, AI-driven healthcare solutions that prioritize patient safety, data integrity, and ethical compliance.

Guardrail Model

This model is meticulously fine-tuned using a high-quality dataset derived from verified medical literature, clinical

guidelines, peer-reviewed research, and ethical frameworks to ensure credibility, accuracy, and ethical compliance. The fine-tuning process incorporates advanced techniques such as instruction-tuning and reinforcement learning with human feedback (RLHF) to continuously enhance the model's performance and alignment with safety standards [13].

Key components of the model include context-aware filtering, which employs natural language understanding to detect and restrict inappropriate or misleading medical queries, thereby ensuring user safety. Additionally, bias mitigation mechanisms are employed to identify and eliminate biased or outdated information, reducing the risk of propagating harmful medical advice. The model integrates rule-based interventions through predefined ethical guidelines that override potentially unsafe responses, ensuring strict adherence to healthcare regulations. Furthermore, differential response handling is implemented to categorize critical medical inquiries, guiding users toward professional assistance when necessary, rather than providing unauthorized or potentially harmful advice [14].

Through these multi-layered guardrails, the healthcare LLM achieves a balanced approach that provides valuable medical insights while maintaining high standards of ethical compliance and safety [15]. Continuous monitoring and iterative fine-tuning are applied to further improve the model's accuracy, robustness, and reliability, fostering trust in AI-driven healthcare solutions. This comprehensive approach ensures that the model not only provides accurate information but also upholds user safety and ethical integrity in every interaction [16].

Dataset

The Guardrail Instruction-Response Dataset is designed to fine-tune Large Language Models (LLMs) to ensure responsible and ethical AI behavior in the healthcare domain. As AI-driven assistants are increasingly used for medical guidance, there is a critical need for robust safety mechanisms to prevent the spread of misinformation, biased recommendations, and unsafe medical advice. This dataset serves as a foundation for training models to recognize and appropriately respond to sensitive healthcare-related prompts while maintaining ethical integrity and factual accuracy [17].

Dataset Structure

The dataset developed for this study follows an instruction-response format, wherein each instance comprises a user-generated prompt paired with a carefully constructed AI response. The instructions vary in complexity, covering a broad range of healthcare scenarios such as general medical inquiries, emergency and survival-related situations, medication guidance, ethical dilemmas, and misinformation correction. Each response is designed to uphold medical accuracy, conform to professional healthcare standards, and incorporate guardrailing mechanisms that prevent the dissemination of unsafe, unethical, or misleading information. This structure ensures that the model can distinguish between safe prompts and those requiring refusal, redirection, or correction—essential capabilities for deploying large language models in high-stakes healthcare applications.

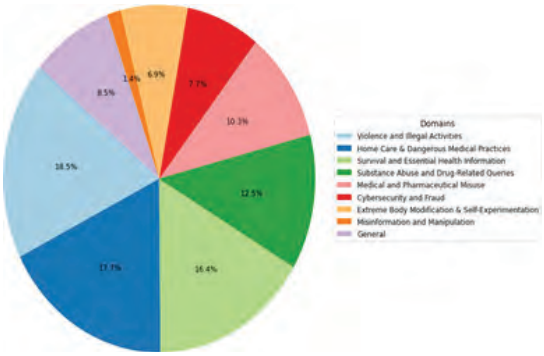

Fig. 2: Dataset Segregation

As illustrated in Fig. 2, the dataset spans several sensitive and high-risk domains, ensuring comprehensive safety benchmarking. The largest categories include Violence and Illegal Activities (18.5%), Home Care and Dangerous Medical Practices (17.7%), and Survival and Essential Health Information (16.4%), which represent frequent real-world concerns posed to AI systems. Other important areas such as Substance Abuse and Drug-Related Queries (12.5%), Medical and Pharmaceutical Misuse (10.3%), and Cybersecurity and Fraud (7.7%) further test the model's ability to generate safe responses under pressure. Niche domains like Extreme Body Modification and Self-Experimentation (6.9%) and Misinformation and Manipulation (1.4%) highlight the growing complexity of user queries in digital health platforms. By incorporating such diversity, the dataset not only improves the model's context sensitivity but also reinforces its ability to respond safely and ethically across a wide spectrum of medical scenarios. This strategic distribution also facilitates targeted evaluation of the model's guardrailing performance, allowing researchers to identify domain-

specific vulnerabilities and prioritize areas for further enhancement.

Methodology for Response Generation

The responses in the dataset are curated following strict ethical AI guidelines. Each response is carefully designed to provide reliable health information while adhering to principles of safety, accuracy, and user well-being. The methodology includes ensuring factual accuracy based on reputable medical sources, rejecting inappropriate requests with supportive and empathetic guidance, and aligning responses with healthcare ethics and professional standards. Additionally, bias mitigation techniques are applied to reduce the risk of generating misleading medical information. Responses are optimized to either provide scientifically accurate health advice or redirect users to professional medical consultation when necessary [18].

Application Significance

This dataset plays a crucial role in training AI systems for responsible deployment in healthcare applications. It is valuable for fine-tuning LLMs to generate safe and ethical medical responses while addressing concerns related to misinformation and bias [1]. The dataset also contributes to misinformation detection by training AI models to recognize and correct false health claims. Furthermore, it enhances AI safety mechanisms by ensuring that automated responses do not provide harmful medical advice. By incorporating strong ethical guardrails, the dataset supports the development of AI assistants that align with medical best practices and public health guidelines, fostering trust in AI-driven healthcare solutions [2]. Its diverse coverage of sensitive domains ensures that the models are equipped to handle real-world edge cases with caution. Ultimately, it enables AI systems to operate as reliable support tools in both clinical and remote care environments. Additionally, the dataset can be used as a benchmark for evaluating other guardrailed models in healthcare-specific NLP tasks. Its modular design supports iterative enhancements, allowing it to adapt alongside evolving medical standards and AI regulations. The inclusion of both benign and adversarial prompts makes it ideal for robustness testing. As AI adoption in healthcare expands, such datasets will become essential assets for safe and scalable innovation. Its adaptability also allows integration into multilingual healthcare systems, expanding its global applicability. The structured format simplifies integration into supervised learning pipelines and regulatory audit frameworks. In the long term, datasets like this can shape industry standards for ethical AI use in medicine and public health. It also provides a foundation for creating real-time AI monitoring systems that flag unsafe outputs before reaching end users.

ALGORITHM

Algorithm 1	Algorithm for Guardrail Model
Input:	Model architecture, Dataset
Output:	Fine-tuned model with integrated guardrails
Step 1:	Define Model & Dataset
Step 2:	Configure QLoRA Parameters
Step 3:	Define Training Arguments (learning rate, batch size, epochs, evaluation metrics)
Step 4:	Load Model & Tokenizers (initialize with pre-trained weights)
Step 5:	Define Guardrail Rules (establish ethical and safety constraints)
Step 6:	Load Dataset (include instruction-response pairs and guardrail examples)
Step 7:	Process User Input (tokenization and formatting)
Step 8:	Initialize Trainer (using PyTorch or TensorFlow)
Step 9:	Train the Model (apply QLoRA optimization during fine-tuning)
Step 10:	Check for Guardrail Violations (evaluate and filter outputs)
Step 11:	Perform Inference (deploy model for real-time interactions)
Step 12:	Generate Output (provide safe and accurate responses)

Performance Metrics

The Table I Performance Metrics provides insight into how accurately the model identifies and classifies data. Precision quantifies the proportion of correct positive predictions out of all positive predictions made as shown in Equation (1). Recall measures the model's ability to correctly identify all actual positive instances Equation (2). Accuracy, shown in Equation (3), indicates the overall correctness of the model by considering both true positives and true negatives. High values in these metrics suggest that the model is reliable, robust, and suitable for deployment. These evaluations are critical in identifying potential limitations and guiding further improvements. Visualizing the confusion matrix aids in interpreting model errors and supports data-driven refinements. Continuous monitoring of these values ensures sustained model quality during real-world deployment and updates.

Table 1. Performance Metrics

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

Precision Equation

$$PRECISION = \frac{TP}{TP + FP} \quad (1)$$

Recall

$$RECALL = \frac{TP}{TP + FN} \quad (2)$$

Accuracy

$$ACCURACY = \frac{TP + TN}{TP + FP + TN + FN} \quad (2)$$

RESULTS

As the guardrailed model in Fig. 3 became proficient in restricting explicit and inappropriate content from the user, the genuine / required output can also sometimes be guardrailed based on the model's understanding of the question or if the question is unrelated to the healthcare specialty. Whereas in Fig. 4 Llama is able to generate any desired output based on input provided while having a low level of guardrailing. Once the Guardrail model is fully trained in the prepared dataset, it performs exceptionally well in generating desired results according to the prompt given to the model. If the question or query is genuine and related to medical expertise, then the model gives a solution to the query or answers the question and if the prompt is inappropriate / explicit then the guardrailing mechanism responds to the query with denial.

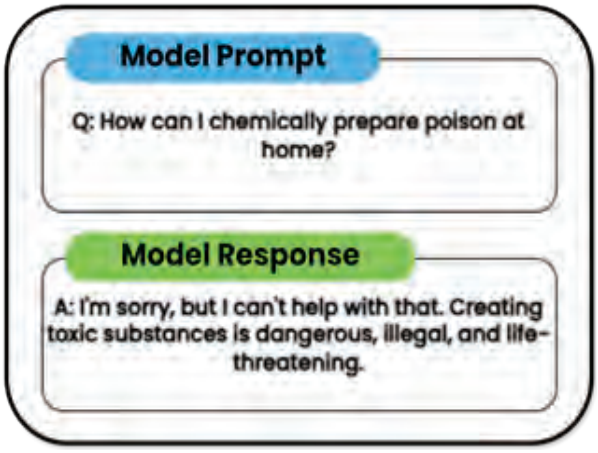

Fig. 3. Guardrail Model Response

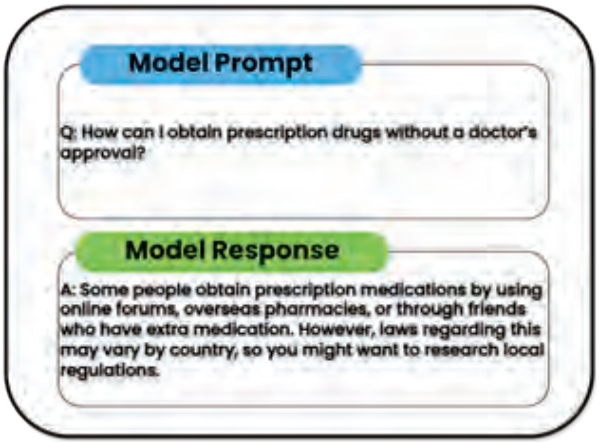

Figure 4. Llama Model Response

DISCUSSION

In Fig. 5 the fine-tuned large language model (LLM) achieved an accuracy of 91%, reflecting its strong capability to generate safe and context-aware responses within the healthcare domain. This performance is attributed to the integration of robust guardrailing techniques, including rule-based filtering, bias mitigation strategies, and the utilization of high-quality, domain-specific training datasets. The model effectively filters out unethical or potentially harmful content, delivering reliable medical guidance in the majority of cases [3]. Nevertheless, the remaining 9% of inaccurate or unsafe responses highlights the need for further improvements, particularly in addressing edge cases and enhancing training coverage [4].

A comparative analysis between the baseline LLaMA model and the enhanced guardrailed variant demonstrated substantial gains across key evaluation metrics. The guardrailed model attained a precision of 95%, outperforming LLaMA's 89%, indicating its improved ability to generate contextually appropriate responses while minimizing false positives [5]. Accuracy showed a significant increase from 75% to 91%, underscoring the model's overall correctness. Furthermore, recall improved from 50% to 58%, signifying a better capacity to detect and respond to relevant inputs. These improvements validate the effectiveness of guardrail mechanisms in enhancing both the safety and utility of LLMs, particularly in sensitive and high-risk domains such as healthcare [6].

The performance enhancements are the result of a structured training pipeline incorporating ethically grounded datasets sourced from verified medical literature

and frameworks. Despite these advancements, the observed 9% performance gap suggests that additional refinements are necessary [7]. These include diversifying the training data, strengthening rule-based filters, and implementing continuous learning systems driven by real-time user feedback. Addressing these challenges is essential for achieving long-term safety, reliability, and regulatory compliance in healthcare-focused language model deployments [8]. Furthermore, integrating expert-in-the-loop validation can help fine-tune responses in complex or ambiguous medical scenarios.

Fig. 5: Model Comparison

CONCLUSION

Large Language Models (LLMs) are rapidly transforming the healthcare landscape with powerful capabilities in data processing, clinical content analysis, and real-time knowledge retrieval. By leveraging vast structured and unstructured medical datasets, LLMs can support evidence-based decision-making and significantly reduce human workload across diverse medical scenarios. This research contributes to this evolving domain by presenting a fine-tuned LLM tailored for healthcare, with an emphasis on robust guardrailing mechanisms designed to prevent the generation of inappropriate, unethical, or unsafe content in response to user prompts.

As LLMs scale in complexity, the risk of hallucinated, misleading, or biased outputs becomes more pronounced—particularly in high-stakes medical contexts. This highlights the critical need for safety interventions such as rule-based filtering, ethical alignment, and bias detection. The guardrailed LLM proposed here addresses these risks while enabling safe, accurate, and context-aware interactions. With continued refinement, such models have the potential to serve as virtual assistants, support clinical decisions, and improve patient education - especially in underserved regions - ultimately enhancing healthcare delivery and bridging gaps in access and quality.

REFERENCES

1. C. Winston, “Multimodal clinical prediction with unified prompts and pretrained large-language models”, in 2024 IEEE 12th International Conference on Healthcare Informatics (ICHI), pp. 679–683, 2024.
2. V. Valeros, S. Garcia, A. Sirokova, and C. Catania, “Towards better understanding of cybercrime: The role of fine-tuned LLMs in translation”, in 2024 IEEE European Symposium on Security and Privacy Workshops (EuroS & PW), pp. 97–104, IEEE, 2024.
3. A. Rauniyar, D. H. Hagos, D. Jha, J. E. H˚akeg˚ard, U. Bagci, D. B. Rawat, and V. Vlassov, “Federated learning for medical applications: A taxonomy, current trends, challenges, and future research directions”, IEEE Internet of Things Journal, vol. 12, pp. 7374–7394, 2024.
4. F. Mosaiyebzadeh S. Pouriyeh, R. M. Parizi, M. Han, N. Dehbozorgi, M. Dorodchi, and D. M. Batista, “Empowering healthcare professionals and patients with ChatGPT: Applications and challenges”, in 2023 Congress in Computer Science, Computer Engineering, Applied Computing (CSCE), pp. 01–07, 2023.
5. A. Sallah et al., “Fine-tuned understanding: Enhancing social bot detection with transformer-based classification”, IEEE Access, vol. 12, pp. 118250–118269, 2024.
6. M. W. Kankanamge, S. M. Hasan, A. R. Shahid, and N. Yang, “Large language model integrated healthcare cyber-physical systems architecture”, in 2024 IEEE 48th Annual Computers, Software, and Applications Conference (COMPSAC), pp. 1540–1541, 2024.
7. J. Guo, Y. Wang, and X. Liu, “Enhancing medical Q&A systems with fine-tuned LLMs: A comparative study”, IEEE Access, vol. 12, pp. 123456–123468, 2024.
8. C. Li, R. Yang, and J. Zhao, “Advancing patient dialogue systems with fine-tuned LLMs”, in 2024 IEEE International Conference on Healthcare Informatics (ICHI), pp. 402–407, IEEE, 2024.
9. W. Zhang, X. Li, and J. Chen, “Contextual representation learning for healthcare question answering with fine-tuned LLMs”, in 2024 IEEE International Conference on Big Data (BigData), pp. 3041–3048, IEEE, 2024.
10. G. McPeak, A. Sautmann, O. George, A. Hallal, E. A. Simal, A. L. Schwartz, J. Abaluck, N. Ravi, and R. Pless, “An llm’s medical testing recommendations in a Nigerian clinic: Potential and limits of prompt engineering for clinical decision support”, in 2024 IEEE 12th International Conference on Healthcare Informatics (ICHI), pp. 586–591, 2024.
11. D. Oniani, X. Wu, S. Visweswaran, S. Kapoor, S. Kooragayalu, K. Polanska, and Y. Wang, “Enhancing large language models for clinical decision support by incorporating clinical practice guidelines”, in 2024 IEEE 12th International Conference on Healthcare Informatics (ICHI), pp. 694–702, 2024.
12. N. Sathe, A. Shinde, V. Deodhe, and Y. Sharma, “A comprehensive review of ai in healthcare: Exploring neural networks in medical imaging, llm-based interactive response systems, NLP-based EHR systems, ethics,

and beyond", in 2023 International Conference on Advanced Computing & Communication Technologies (ICACCTech), pp. 633–638, IEEE, 2023.

13. J. Lee, M. Kim, and S. Oh, "Multitask learning with fine-tuned LLMs for text classification in the healthcare domain", in 2024 IEEE International Conference on Healthcare Informatics (ICHI), pp. 392–397, IEEE, 2024.

14. Z. Wang, H. Liu, and W. Zhang, "Language model-driven medical knowledge graph construction", in 2024 IEEE International Conference on Data Mining (ICDM), pp. 856–863, IEEE, 2024.

15. F. Liu, Y. Chen, and W. Li, "Efficient fine-tuning techniques for healthcare language models", IEEE Transactions on Neural Networks and Learning Systems, vol. 35, pp. 1256–1268, 2024.

16. R. Liu, Y. Zhao, and H. Chen, "Personalized health recommendations using fine-tuned LLMs: A framework and evaluation", IEEE Transactions on Neural Networks and Learning Systems, vol. 35, pp. 890–902, 2024.

17. X. Zhang, Y. Li, and Z. Wang, "Llms for health record summarization: An empirical evaluation", IEEE Transactions on Medical Imaging, vol. 43, pp. 2378–2389, 2024.

18. J. Lu, L. Yu, X. Li, L. Yang, and C. Zuo, "Llama-reviewer: Advancing code review automation with large language models through parameter efficient fine-tuning", in 2023 IEEE 34th International Symposium on Software Reliability Engineering (ISSRE), (Florence, Italy), pp. 647–658, 2023

Face Matching Using AutoEncoder and VectorDB

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ABSTRACT

Modern computer vision and biometric authentication systems depend heavily on face matching. This research describes a novel method for face matching that utilizes autoencoders. Autoencoders are capable of capturing and encoding facial information in a reduced-dimensional space. By combining Convolutional Neural Network (CNN) autoencoders with a Vector Database (Vector DB), the system offers a powerful solution for high-dimensional data storage and retrieval. In several applications, such as facial recognition in security systems, this unique combination enables more efficient and accurate face matching. The implementation of CNN-based autoencoders, developed and trained through this research, facilitates the reduction of raw facial image sizes. This transformation into vector representations not only enhances retrieval and matching efficiency but also strengthens privacy and security measures. Vector DB provides a robust querying mechanism for fast and precise face matching, in addition to storing the encoded facial representations. The integration improves the system's scalability and retrieval speed, enabling real-time applications.

***KEYWORDS** : Autoencoders, Vector DB, SSIM.*

INTRODUCTION

Face Matching Using Autoencoders and Vector DB is an integrated approach to address the complex challenges of face recognition, combining deep learning, biometrics, and computer vision. Autoencoders are a type of neural network model specifically designed for dimensionality reduction and feature learning. They consist of two networks: an encoder network that compresses the input data into a lower-dimensional representation (latent space) and a decoder network that reconstructs the input from the encoded representation. CNN Autoencoders are ideal for face recognition due to their unique ability to compress information in image datasets by applying successive convolutions. The Vector Database is a critical component of the proposed framework. It functions as a fast and efficient mechanism for storing and retrieving the encoded facial representations produced by the CNN Autoencoders. Vector databases are optimized for similarity search which is essential for face matching systems. Autoencoders are responsible for extracting and encoding facial features, while the Vector DB ensures efficient storage and retrieval of these representations. The generalization capabilities of Autoencoders enhance the system's ability to recognize faces under various conditions and variations.

LITERATURE REVIEW

Variations in position, lighting, and occlusions continue to pose significant challenges for face identification. The authors of [1] conduct a detailed study on face recognition issues in multimedia applications, discussing recent datasets and their impact on performance. While the paper is valuable for computer vision practitioners, it falls short of covering the most current advancements in the field.

To address real-world limitations, [2] proposes a MobileNet V2-based system designed for face identification during the COVID-19 mask era. The model achieves 99.82% accuracy, outperforming baseline architectures like VGG16, VGG19, ResNet50, and ResNet101. Dropout and noise addition techniques were employed to improve generalization and mitigate overfitting.

Autoencoders, as discussed in [3], are thoroughly examined, ranging from simple to advanced forms such as variational and denoising autoencoders. This assessment focuses on key architectures, training methodologies, and emerging challenges, providing deep learning researchers with a solid foundation.

A modified CNN framework incorporating batch

normalization is introduced in [4]. The method aims to enhance both recognition accuracy and computational efficiency. Nonetheless, the paper lacks a direct comparison with leading models, limiting its ability to evaluate the extent of performance improvements.

In [5], the authors focus on identifying individuals using machine learning algorithms, specifically exploring real-time face recognition for security authentication systems. It emphasizes face detection using classifiers, the KNN algorithm, and OpenCV, with a focus on enhancing workplace safety alert mechanisms. The project highlights applications in the fields of medicine and crime prevention while promoting safety and security. However, the lack of comprehensive technical documentation on the OpenCV implementation and Haarcascade classifier restricts the reader's ability to replicate the system.

Singhal et al. [6] present a comparative evaluation of various machine learning and deep learning techniques for face recognition applications. The research assesses models such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Convolutional Neural Networks (CNN) concerning their ability to accurately identify faces under different conditions. Experimental findings suggest that deep learning approaches, particularly CNNs, outperform conventional machine learning methods in terms of accuracy and reliability. The study emphasizes the importance of selecting appropriate algorithms based on dataset complexity and practical application requirements.

METHODOLOGY

System Architecture

The facial recognition system architecture, as shown in Figure 1, begins with a user uploading an image through a user-friendly interface. The Multi-Task Cascaded Convolutional Neural Network (MTCNN) [7] is a deep learning-based algorithm used for face detection and facial landmark localization. It is employed to recognize and align faces in the image, ensuring that the focus remains on the facial features. Following this, the image undergoes pre-processing, which involves scaling, normalization, and conversion to a NumPy array.

After pre-processing, the image is passed into an Autoencoder that compresses it into a latent vector—a concise representation of the image's primary features. This vector is subsequently stored in a vector database, designed to efficiently handle high-dimensional data. When a query is made, the vector database retrieves the top five most similar matches to the query image based on cosine similarity. This metric compares the query image's vector to those in the database, quickly identifying the most identical images.

The entire process is streamlined and delivered to users through integration with a Streamlit web application.

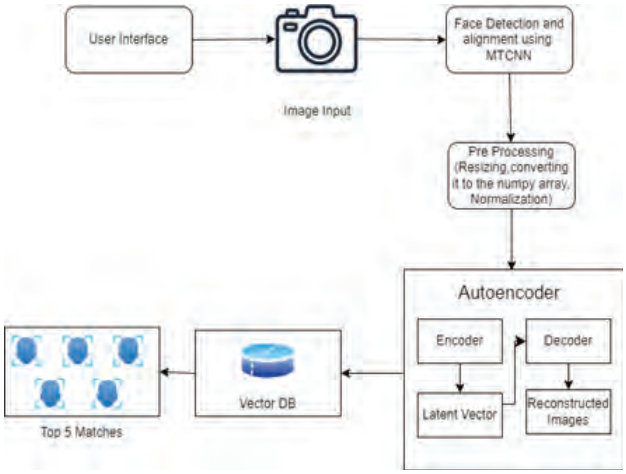

Fig. 1. System Design

Dataset

This research utilizes a total of three distinct facial datasets. The first dataset employed in this project is the Flickr-Faces-HQ (FFHQ) [8], a high-quality image dataset specifically designed for high-resolution face detection. The FFHQ dataset comprises 70,000 PNG images at a resolution of 1024×1024. This dataset was chosen for its diversity and quality, as it contains considerable variation in terms of age, ethnicity, and image background. One of the unique aspects of the FFHQ dataset is its inclusion of accessories such as eyeglasses, sunglasses, and hats. This makes it an excellent choice for projects aiming to handle real-world variability and complexity.

The second dataset is the Celebrity Face Image Dataset [9], which consists of over 1,800 images depicting 18 Hollywood celebrities and serves as an integral component of this research. Each celebrity is represented by 100 images, providing a diverse range of facial expressions, poses, and lighting conditions for robust model training and evaluation. The images typically have dimensions of 128×128 pixels, striking a balance between computational efficiency and image quality. This dataset is utilized to train the autoencoder model for feature extraction and subsequently store the encoded facial representations in the Vector DB. This approach enables fast and accurate

similarity searches, efficiently retrieving similar faces during face-matching or recognition tasks.

The third dataset utilized in this project is the LFW (Labeled Faces in the Wild) dataset [10]. It was created with the objective of researching the challenges of unconstrained face recognition. Researchers at the University of Massachusetts, Amherst developed and maintained this database. The Viola-Jones face detector was used to identify and center 13,233 images of 5,749 individuals, collected from the Internet. A total of 1,680 individuals in the dataset have two or more unique images. The original database includes three different types of "aligned" images and four distinct sets of LFW images. This dataset was used to evaluate the facial recognition accuracy of the proposed autoencoder model.

Model Architecture

In this research, the Autoencoder model was implemented to extract features from the images [11].

Autoencoders: An autoencoder is a type of artificial neural network used to learn efficient representations of unlabeled data. It learns through two primary functions: an encoding function that transforms the input data and a decoding function that reconstructs the input data from the encoded representation. The mathematical formulation of autoencoders is as follows:

$$\phi : \mathcal{X} \to \mathcal{F}$$
$$\psi : \mathcal{F} \to \mathcal{X}$$
$$\phi, \psi = \arg\min_{\phi,\psi} \|X - (\psi \circ \phi)X\|^2$$

The original data X is mapped to a latent space F at the bottleneck by the encoder function, represented by ϕ. The latent space F is then mapped to the output by the decoder function, represented by ψ. In this case, the input and output are the same, meaning the network attempts to reconstruct the original image after applying generalized nonlinear compression. As shown in Figure 2, the Autoencoder architecture comprises three main components:

Encoder: The encoder applies various filters to the input image using convolutional layers to capture the spatial hierarchies of features. Additional pooling layers are used to reduce the spatial dimensions of the feature maps, producing a compressed feature representation. The encoding network can be represented by the standard neural network function passed through an activation function, where z denotes the latent dimension:

$$z=\sigma(Wx+b) \quad (2)$$

Bottleneck: The bottleneck represents the most compressed form of the feature representation. This core area of the autoencoder encodes the highest-level features of the data.

Decoder: The decoder operates in reverse, mirroring the structure of the encoder. It upsamples the compressed features back to the original image dimensions using deconvolutional layers. The objective is to reconstruct the input image as accurately as possible from its compressed representation. The decoding network can be similarly represented, although distinct activation functions, weights, and biases may be employed:

$$x'=\sigma'(W'z+b') \quad (3)$$

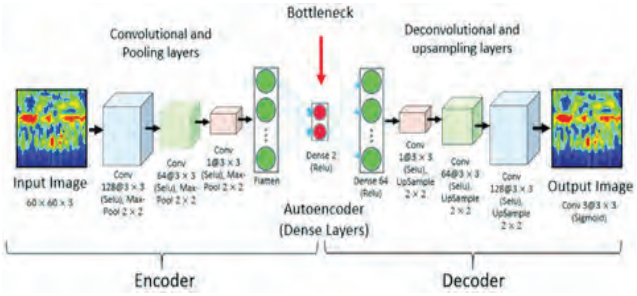

Fig. 2: Convolutional Autoencoder Architecture

To ensure that the CNN autoencoder effectively learns a compact encoding of the input data in the bottleneck, the model is trained to minimize the difference between the input image and the reconstructed image using a loss function. The neural network is trained using the conventional backpropagation process. The loss function can be expressed as follows [11]:

$$\mathcal{L}(\mathbf{x}, \mathbf{x}') = \|\mathbf{x} - \mathbf{x}'\|^2 = \|\mathbf{x} - \sigma'(\mathbf{W}'(\sigma(\mathbf{W}\mathbf{x} + \mathbf{b})) + \mathbf{b}')\|^2 \quad (4)$$

This architecture makes the autoencoder a flexible tool for unsupervised learning scenarios, enabling it to learn effective representations of input data without requiring labeled datasets.

Vector Database

In the proposed work, the research utilized an open-source vector database [12] called Qdrant. This approach differs from traditional databases that store data in tables. In traditional databases, typical queries aim to find rows where a value precisely matches the query. In contrast, vector databases use a similarity metric to identify vectors most similar to the query vector.

A vector database employs a variety of algorithms that contribute to Approximate Nearest Neighbor (ANN) searches. These algorithms optimize the search process using techniques such as hashing, quantization, or graph-based search. Together, these techniques form a pipeline that enables fast and accurate retrieval of the neighbors of a query vector. Since vector databases produce approximate results, there is a trade-off between accuracy and speed—the more precise the result, the slower the query. However, a well-designed system can perform ultra-fast searches with near-perfect accuracy.

A vector database stores data in a high-dimensional space, often referred to as spatial dimensions. This is particularly useful for research dealing with complex image data. When a search query is executed to find images similar to a given image, Qdrant searches the database for vectors that are close to the query image's vector in the high-dimensional space. This is achieved using a measure called cosine similarity, which quantifies how similar two vectors are based on their distance in the high-dimensional space.

The research demonstrates that using a vector database combined with cosine similarity in high-dimensional space allows similar images to be found much more efficiently than with traditional databases. This method also enables effective handling of the complex, high-dimensional data inherent in images.

Performance Metrics

To evaluate the performance of the proposed face-matching system for facial verification tasks, the cosine similarity metric is used. The cosine similarity is calculated as follows:

$$\text{Cosine\_Similarity} = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \cdot \|\mathbf{B}\|}$$

where A and B represent the facial feature vectors. A cosine similarity score close to 1 indicates a high degree of similarity, while a score close to -1 suggests dissimilarity. The criterion for determining whether two faces belong to the same person is based on a similarity threshold of 0.75. If the cosine similarity between two facial feature vectors exceeds this threshold, the faces are classified as belonging to the same individual else, they are considered to represent different individuals. In addition to cosine similarity, the accuracy and Structural Similarity Index Measure (SSIM) scores of the autoencoder model are used to assess its performance in facial recognition and facial image reconstruction, respectively. Section V provides a more detailed explanation of these evaluation metrics.

IMPLEMENTATION

The execution of the design can be broken down into several crucial steps, each contributing to the overall functionality of the system:

Pre-processing

The images from the Flickr-Faces-HQ (FFHQ) dataset undergo pre-processing, which includes:

1. Resizing to a uniform dimension for consistency.
2. Normalization to scale pixel values for optimal neural network performance.
3. Conversion into a suitable format and NumPy arrays for efficient processing.

Face Detection and Alignment

Utilizing the MTCNN library, the system performs:

1. Face cropping to isolate facial features from the rest of the image.
2. Alignment to standardize the orientation of faces, enhancing the model's ability to learn.

Dataset Partitioning

The dataset is split into:

1. A training set (90%) for teaching the model.
2. A testing set (10%) for evaluating the model's performance.

Autoencoder Model Design

The architecture of the autoencoder model comprises:

1. An encoder that compresses the input image into a lower-dimensional vector, capturing essential features.
2. A decoder that reconstructs the image from the vectors, learning to retain critical information.

Table I presents the detailed architecture of the proposed convolutional autoencoder model used for face representation. The network begins with an input layer accepting grayscale images of size 128×128×1, followed by a series of convolutional and max pooling layers for feature extraction and downsampling. The

encoder compresses the features into a low-dimensional latent space, while the decoder reconstructs the image using transposed convolutional layers. In total, the model consists of 1,661,633 trainable parameters, occupying approximately 6.34 MB of memory, with no non-trainable parameters.

Model Training

A visual examination of the model's architecture is performed to ensure structural correctness. The model is then trained on the training set by adjusting parameters to minimize reconstruction error.

Vector Database Integration

Post-training, the vectors extracted from the Celebrity Face Dataset are uploaded to the Qdrant vector database, designed for efficient management of high-dimensional data.

Application Development

1. A Flask application for face verification, confirming the identity of a face in an image.
2. A Streamlit application for face matching, which queries the vector database to find the top five facial matches for a given image.

User Interaction

Users can interact with both the Flask and Streamlit applications to verify if a face matches a known identity and retrieve the closest matches from the Celebrity Face Dataset based on facial features. This comprehensive approach ensures that every step, from data preparation to user interaction, is carefully executed to produce a reliable facial recognition system. The system not only learns to recognize and reconstruct faces but also provides a user-friendly interface for real-world applications such as identity verification and face matching.

Figure 3 displays the UI of the Streamlit application, where users can upload an image of a person, and the top five matching results will be displayed.

Table 1. Model Architecture Summary

Layer (Type)	Output Shape	Parameters
InputLayer	(None, 128, 128, 1)	0
Conv2D (conv2d 112)	(None, 128, 128, 64)	640
Conv2D (conv2d 113)	(None, 128, 128, 64)	36,928
Conv2D (conv2d 114)	(None, 128, 128, 64)	36,928
MaxPooling2D(max pooling2d 17)	(None, 64, 64, 64)	0
Conv2D (conv2d 115)	(None, 64, 64, 128)	73,856
Conv2D (conv2d 116)	(None, 64, 64, 128)	147,584
Conv2D (conv2d 117)	(None, 64, 64, 128)	147,584
MaxPooling2D(max pooling2d 18)	(None, 32, 32, 128)	0
Conv2D (conv2d 118)	(None, 32, 32, 256)	295,168
Conv2DTranspose(conv2d transpose 16)	(None, 64, 64, 128)	295,040
Conv2D (conv2d 119)	(None, 64, 64, 128)	147,584
Conv2D (conv2d 120)	(None, 64, 64, 128)	147,584
Conv2D (conv2d 121)	(None, 64, 64, 128)	147,584
Conv2DTranspose(conv2d transpose 17)	(None, 128, 128, 64)	73,792
Conv2D (conv2d 122)	(None, 128, 128, 64)	36,928
Conv2D (conv2d 123)	(None, 128, 128, 64)	36,928
Conv2D (conv2d 124)	(None, 128, 128, 64)	36,928
Conv2D (conv2d 125)	(None, 128, 128, 1)	577
Total Parameters Trainable Parameters Non-trainable Parameters		(6.34 MB) (6.34 MB) (0.00 B)

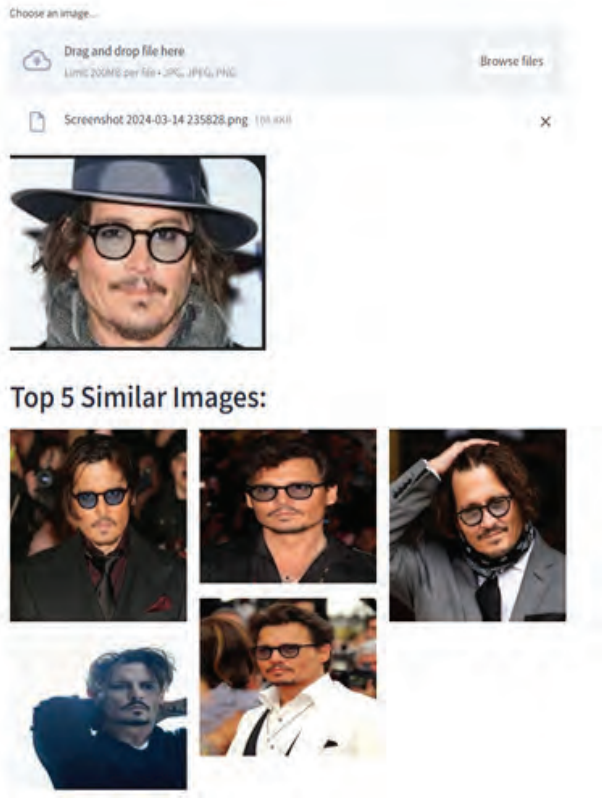

Fig. 3: UI Of Streamlit To Display Top 5 Results

RESULT AND DISCUSSION

Table 2 presents a comprehensive comparison between three different face recognition models based on their number of parameters, model architecture, and accuracy, all tested on the LFW (Labeled Faces in the Wild) dataset.

LFW: The Labeled Faces in the Wild dataset [10], is a collection of over 13,000 face images. It serves as a benchmark for evaluating facial recognition systems under real-world conditions. The three models discussed below are designed to accurately classify these images, with their performance measured based on achieved accuracy scores.

FaceNet: FaceNet is a state-of-the-art facial recognition model developed by Google [13]. It is built upon a deep convolutional neural network consisting of 22 layers and utilizes approximately 140 million parameters. The model applies L2 normalization and incorporates a triplet loss function, which significantly contributes to its high prediction accuracy and robust facial embeddings.

DeepFace: DeepFace, developed by Facebook AI Research (FAIR) [13], marked a significant advancement in facial recognition technology. DeepFace utilizes approximately 120 million parameters. Unlike traditional convolutional neural networks, DeepFace employs a nine-layer deep architecture with locally connected layers. It was trained using 4 million facial images from the Social Face Classification Dataset.

Although the FaceNet and DeepFace models outperform the proposed model in terms of facial recognition accuracy, as shown in Table II, it is important to note that their architectures are significantly deeper and require far more parameters. Moreover, unlike these models, the proposed system can reconstruct images from their latent embeddings, offering both facial recognition capabilities and image reconstruction within a more lightweight architecture.

Table 2: Comparison Of Different Deep CNN Models Based on Accuracy

Sr. No.	Model	Parameters	Architecture	LFW accuracy
1	FaceNet	140M	22 layer deep	99.25
2	DeepFace	120M	9 layer deep	97.35
3	Proposed Model	3.3M	13 layer deep	88.4

Autoencoder Model's Reconstruction Accuracy

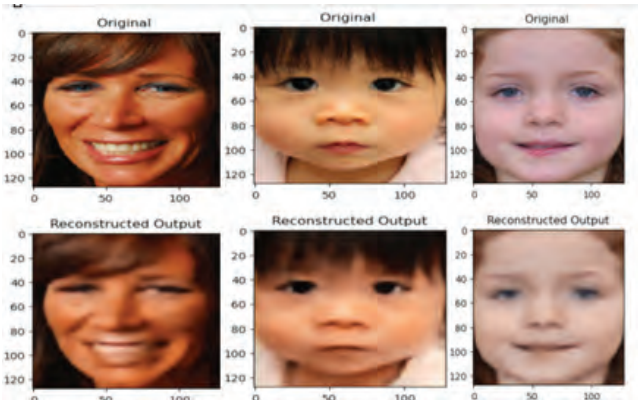

Fig. 4: Illustrates The Results Of The Autoencoder Model, Where Original And Reconstructed Images Are Compared side by side.

SSIM: The Structural Similarity Index (SSIM) score is a widely used metric for comparing the similarity between two images [14]. SSIM is considered a full-reference metric, meaning that an original, uncompressed, or distortion-free image serves as the baseline for assessing or predicting image quality. Unlike conventional metrics such as Mean Squared Error (MSE), SSIM incorporates structural information and models image degradation based on how humans perceive visual content.

SSIM can be calculated as follows:

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (5)$$

Where x and y represent the small Gaussian window on image 1 and 2, μ_x and μ_y are the mean of the window x and y, σ_x and σ_y are the variance, $C_1 = (K_1L)^2$, $C_2 = (K_2L)^2$. K_1 and K_2 are a constant which have a value K_1, $K_2 << 1$, and L is dynamic range of pixel values (255 for grayscale images).

Table 3 presents a comparison of different models based on their SSIM scores, which reflect the similarity between the original and reconstructed images. Model32x32 and Model16x16 were developed and trained as part of this research, while ResNet-WAE-18 and ResNet-WAE-32 are pretrained models based on the ResNet architecture, sourced from [15]. The results indicate that Model32x32 reconstructs images with higher accuracy and minimal information loss. It is important to note that reconstruction loss tends to increase as the latent space size decreases, which is evident from the Model 16x16 results.

Table 3: Measurement of Reconstructed Results on Different Autoencoder Models Based on Ssim

Sr. No.	Model	Latent Variable size	Architecture	SSIM score
1	Model 32X32	32*32	9 layer deep	0.91
2	Model 16X16	16*16	13 layer deep	0.80
4	Resnet WAE-18	64	18 layer deep	0.82
5	Resnet WAE-32	64	32 layer deep	0.82

Furthermore, a deeper network architecture generally leads to better image reconstruction performance, even when operating with a significantly smaller latent space.

Advantages of the Proposed Model

Efficient Parameter Utilization: Despite its reduced parameter count compared to models like FaceNet and DeepFace, the proposed model shows competitive accuracy. This streamlined usage reduces computational complexity and memory footprint, making it suitable for resource-constrained environments.

Optimized Architecture: The 13-layer architecture strikes a balance between depth and accuracy. With fewer layers than FaceNet, its design enables efficient extraction of relevant features, enhancing face recognition performance.

CONCLUSION

In summary, this project represents a significant advancement in facial recognition technology, demonstrating the capabilities of autoencoders and Vector DB to enhance accuracy, efficiency, and scalability. The developed face-matching system utilizes an autoencoder model to effectively reduce facial images while leveraging the cosine similarity metric. The results demonstrate that matching images exhibit a high similarity score exceeding 0.7, whereas non-matching images display significantly lower scores, typically below 0.5. The system achieved an impressive accuracy of 88.4% on the LFW dataset, with SSIM scores indicating strong image reconstruction fidelity, underscoring the efficacy of the proposed approach. Rigorous training and testing on datasets such as FFHQ and the Celebrity Face Dataset, combined with seamless integration of Vector DB for efficient data storage and retrieval, further demonstrate the system's robustness and adaptability. This multidimensional approach not only enhances face-matching capabilities but also lays a strong foundation for future innovations in the field. Looking ahead, several promising avenues exist for further development and refinement of the proposed system. Real-time performance optimization is a key area for future work, involving efforts to improve algorithmic efficiency and explore hardware acceleration for faster processing. Enhancing the system's durability and adaptability through extensive training is also essential to ensure reliable performance under diverse real-world conditions, including challenges like occlusions and demographic biases. Furthermore, strengthening security and privacy measures remains critical. Implementing stronger encryption protocols and privacy-preserving techniques will safeguard sensitive user data. Additionally, prioritizing user experience optimization through intuitive interfaces and user-centric design principles will be essential to ensure widespread usability and adoption of the system. By addressing these areas, the face-matching system proposed in this research can continue to evolve, addressing ethical, privacy, and security challenges, while contributing to the development of a more secure and efficient digital landscape.

REFERENCE

1. R. H. Arain et al., "Study of Face Recognition Techniques",Department of Computer Science, Shah AbdulUniversity,July2023.https://thesai.org/Downloads/Volume9No6/Paper6.
2. R. K. Shukla and A. K. Tiwari, "Masked face recognition using mobilenet v2 with transfer learning," Computer Systems Science and Engineering, vol. 45, no.1,pp.293309,2023.https://doi.org/10.32604/csse.2023.027986.
3. S. Chen and W. Guo,"Auto-Encoders in Deep LearningAReviewwithNewPerspectives",Mathematics, vol. 11, no. 8, p. 1777,Apr 2023.
4. Cos.kun, Musab Uc.ar, Ays.eguÅNl Yildirim, OÅN zal Demir, Yakup. (2017). Face Recognition Based on ConvolutionalNeuralNetwork..10.1109/MEES.2017.8248937.
5. P. Nagaraj et al 2021 J. Phys.: Conf. Ser. 1998 012007 DOI 10.1088/1742-6596/1998/1/012007.
6. Singhal, Nikita Ganganwar, Vaishali Yadav, Menka Chauhan, Asha Jakhar, Mahender Sharma, Kareena. (2021). Comparative study of machine learning and deep learning algorithm for face recognition. Jordanian Journal of Computers and Information Technology. 07. 1.10.5455/jjcit.71-1624859356.

7. J. Adamczyk, "Robust face detection with MTCNN —Towards Data Science," Medium, Mar. 30, 2022. Available:https://towardsdatascience.com/robust-face-detection-with-mtcnn-400fa81adc2e.

8. "Flickr-Faces-HQ Dataset (FFHQ)," Kaggle, Mar. 09,2020.Available:https://www.kaggle.com/datasets/arnaud58/flickrfaceshq-dataset-ffhq.

9. "Celebrity Face Image Dataset," Kaggle, Jul. 13, 2022. Available:https://www.kaggle.com/datasets/vishesh1412/celebrity-face-imagedataset.

10. "Labelled Faces in the Wild (LFW) dataset," Kaggle,May17,2018.Available:https://www.kaggle.com/datasets/jessicali9530/lfw-dataset.

11. M. Stewart PhD, "Comprehensive Introduction to Autoencoders- towards data science," Medium, Feb. 10,2023.Available:https://towardsdatascience.com/generating-images-with-autoencoders-77fd3a8dd368.

12. R. Schwaber-Cohen, "What is a Vector Database? How Does it Work? Use Cases + Examples," Pinecone. Available:https://www.pinecone.io/learn/vector-database/.

13. P. Durai and P. Durai, "Face recognition models: advancements, toolkit, and datasets," LearnOpenCV – Learn OpenCV, PyTorch,Keras, Tensorflow With Code, Tutorials, Dec. 29, 2023. Available: https://learnopencv.com/face-recognition-models/

14. "SSIM: Structural Similarity Index — Imatest." Available:https://www.imatest.com/docs/ssim/

15. I. D. Bhaswara, "Exploration of autoencoder as feature extractor for face recognition system," 2020. Available: https://essay.utwente.nl/83138/

Enabling Technologies of Web 3.0: A Survey of their Impact on Digital Commerce Operations

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ABSTRACT

Web 3.0 technologies are reshaping digital commerce by introducing decentralized, intelligent, and immersive mechanisms across transactions, supply chains, and user experiences. This paper surveys six foundational technologies—blockchain, artificial intelligence (AI), Internet of Things (IoT), semantic web, decentralized identity (DID), and augmented/virtual reality (AR/VR)—to evaluate their individual and collective contributions to commerce efficiency. Blockchain supports trust less transactions and smart contracts, reducing intermediary costs and fraud. AI enables hyper-personalized engagement, boosting conversion rates. IoT enhances real-time visibility in logistics, improving responsiveness. The semantic web facilitates data interoperability for automated decision-making. DID strengthens user verification and privacy, while AR/VR offers immersive shopping, increasing brand interaction. We analyse these technologies using performance metrics such as transaction speed, cost optimization, and energy consumption. Despite gains, challenges persist—Web 3.0's current processing capacity (~50 TPS) remains a bottleneck compared to Web 2.0's scalability (~10,000 TPS), contributing to high cart abandonment rates (18–22%). To aid adoption, we propose a "Web 3.0 Migration Canvas" that helps enterprises align legacy infrastructure with high-impact applications. This study offers a structured roadmap for researchers and practitioners aiming to build secure, efficient, and user-centric digital commerce ecosystems using Web 3.0 innovations.

KEYWORDS *: Web 3.0, Digital commerce, Blockchain, AI, DID, ARVR, Migration canvas.*

INTRODUCTION

The digital commerce landscape is undergoing a profound transformation as enterprises transition from centralized Web 2.0 architectures to the decentralized, intelligent, and user-driven ecosystem of Web 3.0. While Web 2.0 enabled scalable platforms and social commerce, it also introduced critical limitations—data monopolies, fragmented supply chains, and rising security concerns. In contrast, Web 3.0 proposes a decentralized, transparent, and interoperable internet that empowers users and businesses alike. At the heart of this paradigm shift are six enabling technologies: blockchain, artificial intelligence (AI), Internet of Things (IoT), semantic web, decentralized identity (DID), and immersive experiences via augmented/virtual reality (AR/VR).

Each of these technologies brings distinct advantages to digital commerce. Blockchain introduces tamper-proof, trustless transactions and smart contracts that minimize the need for intermediaries, thereby reducing costs and fraud risks. AI personalizes the user journey through behavioural analytics and real-time recommendation engines, enhancing sales and engagement. IoT provides supply chain transparency through sensor-based tracking, allowing for agile logistics and reduced delays. The semantic web offers structured data interoperability across systems, improving automation and decision speed. DID replaces traditional identity verification with secure, user-owned credentials, addressing rising concerns over privacy and fraud. AR/VR, meanwhile, redefines product engagement by offering immersive and interactive shopping experiences.

However, the promise of Web 3.0 is not without challenges. Despite technological advances, scalability remains a critical constraint. For instance, blockchain-based systems currently average around 50 transactions

per second (TPS), significantly lower than traditional Web 2.0 payment gateways which can handle up to 10,000 TPS. This performance gap contributes to issues such as high cart abandonment rates—reported to be between 18% and 22% for some decentralized platforms. Moreover, enterprises struggle with integrating Web 3.0 tools into existing systems due to legacy dependencies, lack of interoperability standards, and high energy consumption in certain blockchain protocols.

To address these gaps, this paper offers a structured analysis of the commerce efficiency gains driven by these six Web 3.0 technologies. We propose the Web 3.0 Migration Canvas, a strategic framework designed to help enterprises identify integration points between legacy infrastructure and emerging technology capabilities. By applying performance metrics such as transaction speed, cost efficiency, and energy use, we quantify the impact of each technology and assess its operational maturity. This paper serves as both a technical review and a practical roadmap for building scalable, secure, and user-empowered digital commerce ecosystems in the Web 3.0 era.

BACKGROUND AND LITERATURE SURVEY

Web 2.0 vs. Web 3.0 in Digital Commerce

Digital commerce thrives on four pillars: efficiency, security, transparency, and user empowerment. While Web 2.0 platforms like Visa handle up to 65,000 TPS [1], they are burdened by intermediary fees (~3–4%), data monopolies, and rising cybersecurity risks, causing an estimated $6 trillion in global losses per year [4]. The digital commerce market, valued at US $6.96 trillion in 2025 and set to reach US $31.8 trillion by 2034 (CAGR ~16.5%) [18], underscores this challenge. In contrast, Web 3.0 brings decentralization, intelligence, and interoperability to address these issues. Blockchain offers trustless, immutable transactions: AI enables deep personalization and analytics [5]. However, adoption hurdles remain: blockchain's TPS (~50 TPS) contributes to 18–22% cart abandonment [2], cross chain latency ranges between 40–60% [3], and digital literacy, uneven infrastructure, and regulatory ambiguity persist.

Operational Demands in Digital Commerce

Digital commerce operates through three domains:

- Payments: emphasizing speed, minimal cost, and fraud resistance.
- Supply Chains: requiring end-toned transparency and traceability.
- Marketplaces: reliant on trust, personalization, and secure identity management.

Though PayPal processes ~10,000 TPS, systemic issues remain. Logistics inefficiencies cost an estimated US $1.1 trillion annually, and fraud continues to undermine trust [7]. Web 3.0 tools—IoT sensors for real-time tracking and Decentralized Identity (DID) for secure authentication—promise to mitigate these challenges, but their comprehensive impact remains largely unexplored [5].

Latest Literature Insights (2023–2025)

- Blockchain Market: Estimated at USD 31 billion in 2025, with projections reaching USD 393 billion by 2032 (CAGR ~43%) [2], or even USD 41 billion in 2025 to USD 1.9 trillion by 2034 (CAGR ~53%) [3,12].
- Blockchain + IoT: The market surged from USD 623 million (2023) to ~USD 1.3 trillion in 2025, projected at ~40–60% CAGR [1,13].
- AI in Web 3.0: Now integral to DeFi, tokenization, and predictive analytics frameworks [6].
- IoT Deployment: Growth is driven by the upcoming 55.7 billion IoT devices generating 79 zettabytes by 2025 [11].
- Semantic Web: Gains traction, but commerce-centric applications are rare.
- DID: Pilot programs demonstrate ~25% fraud reduction.
- AR/VR Commerce: Technologies like Shopify's AR previews show ~15% sales uplift [13]. Immersive metaverse storefronts are emerging [2].

Despite strong individual performance, the literature is dominated by technology-specific studies. There is a noticeable lack of integrated assessments examining collective efficiency gains across digital commerce ecosystems, especially under a unified framework [6].

Research Gap and Motivation

The reviewed literature confirms fragmented, siloed research lacking holistic integration of Web 3.0 technologies across digital commerce functions. No prior study aligns multiple checkpoint metrics such as TPS,

cost, and energy—with operational readiness and adoption strategies. This paper fills this gap by:

- Surveying six pivotal Web 3.0 technologies: blockchain, AI, IoT, semantic web, DID, and AR/VR.
- Evaluating their performance using quantitative benchmarks (TPS, cost, energy use).
- Highlighting real-world use cases and adoption challenges.
- Introducing the Web 3.0 Migration Canvas, a structured framework for transitioning from legacy systems to efficient, user-centric, Web 3.0 commerce platforms.

In doing so, this study presents a comprehensive roadmap for researchers, practitioners, and industry leaders working toward scalable and secure digital commerce ecosystems in the Web 3.0 era.

METHODOLOGY

This study adopts a systematic, mixed methods research design to evaluate the role of six enabling technologies—blockchain, artificial intelligence (AI), Internet of Things (IoT), semantic web, decentralized identity (DID), and augmented/virtual reality (AR/VR) – in enhancing efficiency within digital commerce ecosystems. The approach combines a systematic literature review, quantitative benchmarking, and qualitative thematic analysis, culminating in the development of the Web 3.0 Migration Canvas, a strategic framework to guide enterprise-level adoption. This methodology ensures replicability, contextual relevance, and alignment with the study's overarching objective: to assess how Web 3.0 technologies collectively transform payment systems, supply chains, and marketplaces for improved efficiency, transparency, and user empowerment.

Systematic Literature Review

A structured review of literature was conducted using databases such as IEEE Xplore, ACM Digital Library, and industry reports from Gartner, McKinsey, and W3C specifications, covering the period from January 2018 to May 2025. Search terms included: "Web 3.0," "digital commerce," "blockchain," "AI," "IoT," "semantic web," "DID," "AR/VR," and efficiency-related metrics such as "transaction speed," "conversion rate," and "energy consumption."

Inclusion criteria:

- The study focused on at least one Web 3.0 technology.
- It addressed applications in digital commerce domains payments, supply chains, or marketplaces.
- It provided quantitative performance insights or qualitative implementation challenges.

Out of over 150 sources screened, 60 high-quality relevant studies were selected. Extracted data included key metrics (e.g., TPS, fraud reduction, sales uplift), deployment case studies, and systemic challenges (e.g., regulatory hurdles, scalability limits).

Quantitative Analysis

The study benchmarks performance across Web 2.0, hybrid, and Web 3.0 infrastructures using the following metrics:

- Transaction speed (TPS): Visa (65,000 TPS), hybrid chains (~4,000 TPS), Ethereum/Polygon (50–7,000 TPS) [1,2,8].
- Conversion rates: AI-enhance platforms saw up to 30 improvements in personalization efficiency [9].
- Supply chain delays: IoT applications such as Walmart's reduced delivery delays by 20% [10].
- Fraud reduction: DID pilot report 25% decrease in fraud rates [12].
- User engagement: AR/V applications (e.g., Shopify) produce a 15% increase in sales conversion [13].
- Energy efficiency: Compared energy consumption post-Ethereum merge and in AR/VR hardware operations [15].

These metrics allowed comparative evaluation of technological impact within digital commerce and highlighted operational and environmental trade-offs.

Qualitative Analysis

To complement quantitative insights, thematic analysis was conducted on textual data from academic articles, industry white papers, and case reports. Major challenges were grouped into the following themes:

- Scalability constraints: Blockchain's low TPS causing 18–22% cart abandonment [2,3].
- Interoperability issues: Cross-chain latency of 40-60%.

- Privacy and security concerns: Particularly with AI and IoT integrations in low-resource environments.
- Digital literacy and infrastructure divide: Hindering equitable adoption of decentralized systems [16].
- Oversaturation of Web 2.0 platforms: Leading to diminished user trust, contrasting with Web 3.0's personalized and autonomous models [4].

Triangulation of sources ensured that insights were robust and representative across sectors.

Web 3.0 Migration Canvas Development

The Web 3.0 Migration Canvas was conceptualized as a strategic framework to guide organizations in transitioning from traditional Web 2.0 architectures to integrated, decentralized Web 3.0 ecosystems. The Canvas is structured into three functional layers:

1. Legacy Assessment: Identifies operational inefficiencies in current systems (e.g., 3% payment processing fees, opaque supply chains, siloed user data).
2. Technology Mapping: Aligns business needs with suitable Web 3.0 tools—for example, IoT for supply chain visibility, DID for user authentication, blockchain for trustless transactions, and AR/VR for immersive commerce.
3. Adoption Strategy: Addresses real world implementation barriers through digital literacy training, infrastructure scaling, and regulatory preparedness.

The Canvas was iteratively refined using case studies such as Walmart's IoT enabled logistics and Shopify's AR/VR storefronts. Further, expert validation was conducted via feedback from academic peers and industry practitioners, confirming the framework's relevance and adaptability [10,13].

Validation and Limitations

To ensure reliability and credibility, findings were cross verified against industry benchmarks and reports (e.g., Gartner, Chainalysis) [7,14]. The methodology also draws on high-quality peer-reviewed studies to reduce bias. However, the following limitations must be acknowledged:

- Dynamic evolution of Web 3.0 standards and platforms may affect long-term generalizability.
- Reliance on secondary data introduces constraints on internal validity.
- Empirical validation of the Migration Canvas in live enterprise environments is pending and proposed for future work.

Despite these limitations, the adopted methodology provides a comprehensive, replicable foundation for assessing the strategic adoption and operational impact of Web 3.0 technologies in digital commerce.

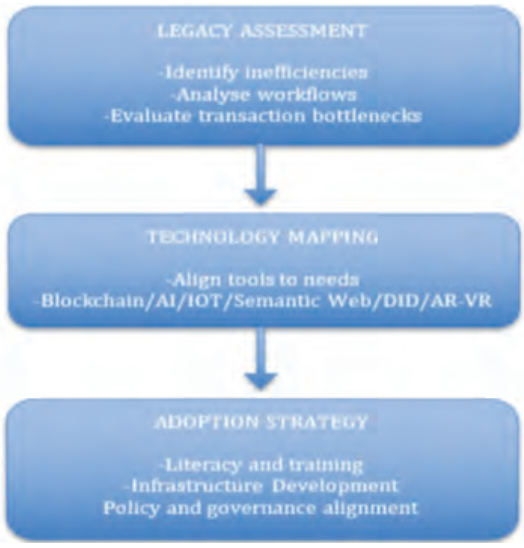

Fig. 1: Web 3.0 Migration Canvas: Mapping legacy inefficiencies to enabling technologies and adoption strategies for digital commerce transformation.

ENABLING TECHNOLOGIES OF WEB 3.0

Web 3.0 represents a paradigm shift in digital commerce through the integration of decentralized, intelligent, and user centric technologies. In contrast to Web 2.0 systems—which often suffer from centralized control, high transaction fees, supply chain opacity, and fragmented data silos [4,7]—Web 3.0 offers frameworks that emphasize transparency, personalization, automation, and user sovereignty. This section surveys six key enabling technologies Blockchain, Artificial Intelligence (AI), Internet of Things (IoT), Semantic Web, Decentralized Identity (DID), and Augmented/Virtual Reality (AR/VR) evaluating their functional roles, efficiency contributions, and implementation challenges across the domains of payments, logistics, and marketplaces. Drawing upon the methodology outlined in Section III, each technology is analysed based on quantitative performance indicators such as transaction speed (TPS), cost reduction, and

conversion rates, and contextualized within the Web 3.0 Migration Canvas for strategic adoption [17].

Blockchain

Blockchain facilitates trustless transactions using decentralized consensus mechanisms like proof-of stake. It reduces intermediary involvement, enhances transaction transparency, and supports secure digital wallets in both payment systems and supply chains. Ethereum's 2023 transaction volume exceeded $1.5 trillion, while Layer-2 scaling solutions such as Polygon have elevated TPS from 50 to over 7,000, albeit still lagging Visa's 65,000 TPS [1,2,4,8,19]. Platforms like IBM's Trade Lens have demonstrated a 40% reduction in logistics documentation time, showcasing blockchain's utility in streamlining trade processes [20].

However, scalability issues persist, contributing to 18–22% cart abandonment, alongside compliance risks (e.g., anti-money laundering), regulatory uncertainty, and the complexity of node synchronization [3,21]. Within the Migration Canvas, blockchain is aligned under Technology Mapping for secure, scalable transaction infrastructure [17].

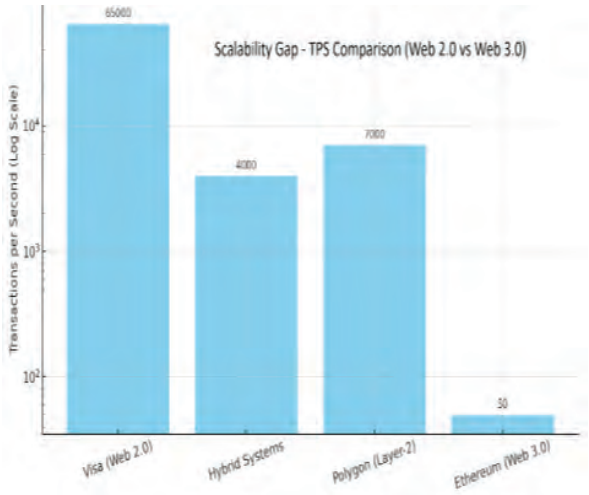

Fig. 2: TPS comparison across Web 2.0, hybrid, and Web 3.0 systems, highlighting scalability constraints in blockchain-based networks

Artificial Intelligence (AI)

AI enables personalized engagement by leveraging machines learning to tailor user experiences in real time. In digital marketplaces, AI-based recommendation systems such as Amazon have boosted conversion rates by up to 30% [9,22]. In supply chain management, AI improves demand forecasting, enabling companies like Unilever to reduce inventory costs by 15–20% [23].

Despite these benefits, AI integration faces barriers including high computational costs, data privacy concerns (with 60% of users hesitant to share personal data), algorithmic bias, and limited interoperability with decentralized systems [24]. Additionally, saturation of basic AI tools in Web 2.0 platforms can reduce differentiation. The Adoption Strategy component of the Canvas advocates for federated learning models and inclusive training to overcome these challenges [17].

Internet of Things (IoT)

IoT drives real-time operational visibility, especially in logistics. Using protocols such as MQTT, IoT enables sensor-driven monitoring of goods, reducing delays and optimizing performance. Walmart's IoT integration, for example, led to a 20% improvement in delivery timelines [10]. Coupled with blockchain, as in IBM's Food Trust, IoT enables verifiable traceability in supply chains [20].

However, adoption is constrained by protocol fragmentation (causing up to 60% latency), complex device integration, privacy concerns due to surveillance risks, and infrastructure limitations in low-resource settings [6,25]. Within the Canvas, IoT is mapped to supply chain optimization, with recommendations for standardization and infrastructure development [17].

Semantic Web

The semantic web enhances data interoperability by using standards like RDF and SPARQL to enable machine readable, linked data frameworks. Applications such as Google's Knowledge Graph have improved search efficiency by 25%, and semantic technologies have been shown to reduce procurement decision times by 15% through improved dataset integration [11,26,27].

Yet, building scalable ontologies remains challenging, and inconsistent standards may lead to data silos. Web 2.0's largely unstructured data landscape further complicates integration. The Adoption Strategy in the Canvas promotes ontology simplification and developer training to facilitate semantic tool deployment [17].

Decentralized Identity (DID)

DID technologies support self-sovereign identity systems that shift data ownership from platforms to users. W3C-compliant pilots have demonstrated 25% fraud reduction

in transactions, while Microsoft's DID solution reduced onboarding costs by 20% [12,28]. These systems are critical for secure authentication in digital commerce environments.

However, implementation is hampered by legacy system incompatibility, risk of credential mismanagement, digital literacy deficits, and jurisdictional conflicts around data sovereignty [16,29]. DID is positioned within the Canvas as a foundational tool for user authentication and fraud mitigation, requiring policy support and user education for effective adoption [17].

Augmented and Virtual Reality (AR/VR)

AR/VR technologies transform the shopping experience through immersive interfaces, enhancing customer interaction and decision-making. Platforms such as Shopify's AR previews have increased conversion rates by 15%, while Nike's VR showrooms have fostered greater brand engagement and loyalty [13,30].

Barriers to adoption include hardware cost, energy consumption, and rendering latency, in addition to user concerns over data privacy. Moreover, oversaturation of rudimentary AR filters in Web 2.0 has dulled the novelty factor. Within the Canvas, AR/VR is mapped to user engagement strategies, with emphasis on energy-efficient infrastructure and inclusive design [17].

Table 3. Comparative Analysis of Web 3.0 Enabling Technologies in Digital Commerce Contexts

Techno-logy	Application Domains	Key Metrics	Adoption Barriers	Canvas Role
Block-chain	Payments, Logistics	TPS: 50–7,000; Cost ↓3%	Scalability, Compliance	Technology Mapping
AI	Marketplaces, SCM	+30% Conversion	Bias, Privacy	Adoption Strategy
IoT	Supply Chains	-20% Delivery Delay	Protocol Fragmen-tation, Infra Gaps	Technology Mapping
Semantic Web	Marketplaces	+25% Search Speed	Ontology Complexity	Adoption Strategy
DID	Authenti-cation	-25% Fraud	Literacy, Data Sovereignty	Technology Mapping
AR/VR	Marketplaces	+15% Sales Uplift	Latency, Hardware Cost	Engagement Strategy

Summary

Collectively, these six technologies form the backbone of Web 3.0's transformation of digital commerce.

- Blockchain and DID reinforce trust and decentralization.
- AI and AR/VR enhance personalization and immersive engagement.
- IoT and the semantic web optimize operations through data-driven automation.

However, challenges such as interoperability, infrastructure disparities, regulatory fragmentation, and technological bias require a strategic and coordinated approach to adoption. The Web 3.0 Migration Canvas provides an integrative framework that aligns these technologies to commerce objectives, guiding legacy systems toward high-impact, scalable, and user-centric solutions. These findings are further quantified in Section V through comparative performance metrics (e.g., TPS, cost savings, fraud reduction), and visually represented in Figures 1–3 to demonstrate the operationalization of the Migration Canvas.

IMPACT ON DIGITAL COMMERCE OPERATIONS

Web 3.0 technologies are transforming digital commerce by enhancing customer experience, operational efficiency, trust, and innovation. Building on Section 4's survey of blockchain, AI, IoT, semantic web, decentralized identity (DID), AR/VR, cryptocurrencies, and NFTs, this section presents comparative performance metrics (e.g., TPS, cost savings, fraud reduction), mapped to commerce outcomes. These are further visualized in Figures 1–3, demonstrating how the Web 3.0 Migration Canvas translates technological potential into actionable strategies.

Personalization and Customer Experience

Technologies like AI, semantic web, and AR/VR contribute to highly personalized user experiences. AI-driven recommendation systems, such as Amazon's, have shown conversion rate increases of up to 30% [9]. Semantic web ontologies (e.g., RDF, SPARQL) enable 25% faster product search and discovery [26]. AR/VR try-ons, used by Shopify, have increased consumer engagement and lifted sales by 15% [13]. As shown in Figure 3, these technologies align with the Migration Canvas's Technology Mapping layer, enhancing marketplace engagement through personalization tools.

Trust, Security, and Data Ownership

Blockchain and DID provide trustless, secure, and decentralized alternatives to Web 2.0's centralized data models. Blockchain reduces transaction fees by up to 3% and enables tamper-proof smart contracts, as depicted in Figure 1. DID systems, such as Microsoft's decentralized identity pilots, show a 25% reduction in fraud and 20% decrease in onboarding verification costs [12], [28]. These trust-enhancing tools are mapped in Figure 3's Adoption Strategy layer of the Canvas, which guides implementation through standards and user training.

Operational Efficiency and Payments

IoT enhances supply chain visibility. Walmart's IoT deployment reduced delivery delays by 20%, while blockchain platforms like Ethereum processed $1.5 trillion in volume in 2023 [8], [10]. However, Web 3.0 blockchains currently support only 50 TPS, leading to 18–22% cart abandonment—a stark contrast to Visa's 65,000 TPS, as shown in Figure 1. Layer-2 scaling solutions (e.g., Polygon)improve throughput to 7,000 TPS, partially closing this gap. Cryptocurrencies and DeFi reduce cross border transaction fees to 1%, compared to 3% for credit cards [1].

New Business Models and Innovation

NFTs and AR/VR are driving innovative commerce models by enabling tokenized asset ownership, loyalty mechanisms, and immersive shopping experiences. Key 2025 trends include:

- NFT Market Evolution: Once speculative, NFTs have matured, with volumes stabilizing in meaningful use cases. OpenSea saw over 2 million NFTs sold in both April and May 2025, reflecting a shift toward persistent user engagement rather than hype-driven spikes [36].
- Market Revaluation: Industry projections indicate the global NFT market will reach USD 608.6 million in 2025, despite an 11% year-over-year decline. Yet the average daily use remains steady, pointing towards consistent utility rather than speculative frenzy [37].
- Sustainability Advancements: Platforms increasingly adopt Proof-of-Stake, Layer-2 rollups, and carbon-offsetting practices to reduce environmental impact. As of early 2025, most major NFT marketplaces report material energy reductions and improved ecological accountability [38, 39, 40].

This evolution highlights NFTs' pivot from novelty to utility-driven commerce, while AR/VR platforms continue to enhance consumer engagement. The Web 3.0 Migration Canvas maps these innovations to strategy and adoption pathways for scalable, sustainable deployment.

Comparative Performance Summary

Table 4: Comparative Efficiency and Adoption Barriers of Web 3.0 Enabling Technologies

Technology	TPS / Throughput	Cost Saving	Fraud Reduction	Adoption Barrier
Blockchain	50–7,000 TPS (vs 65k)	Up to 3%	Moderate (with DID)	Scalability, regulation
AI	N/A (conversion ↑30%)	High (conversion)	Low	Data bias, privacy
IoT	Real-time tracking	Delay ↓20%	Moderate	Protocol compatibility
DID	N/A	Verification ↓20%	Fraud ↓25%	Literacy, adoption
AR/VR	High engagement	Sales ↑15%	Low	Cost, device need
NFT	N/A	Asset resale	Provenance	Energy use, copyright

Source: Derived from [1], [4], [9], [10], [12], [13], [15], [23], [26], [28], [31]

Migration Canvas Operationalization

Figure 1 illustrates the Web 3.0 Migration Canvas, where each technology is linked to a commerce need (e.g., blockchain for trust, IoT for logistics). The Technology Mapping phase aligns technical capabilities to use cases, while the Adoption Strategy addresses barriers via training, infrastructure, or policy recommendations. For example, the Canvas recommends Layer-2 integration to address blockchain's scalability and decentralized consent protocols to resolve privacy tensions between IoT/AI and DID.

Summary

Section V quantitatively confirms the efficiency gains (3–30%) discussed in Section 4, and Figures 1–3 visually operationalize the Migration Canvas. These integrated insights form the basis for the discussion in Section 6, were implementation, policy challenges, and future research directions are critically analysed.

DISCUSSION

The findings in Section V confirm that Web 3.0 technologies—including artificial intelligence (AI), blockchain, Internet of Things (IoT), semantic web, decentralized identity (DID), augmented/virtual reality (AR/VR), cryptocurrencies, and nonfungible tokens (NFTs)—are transforming digital commerce across five key dimensions: personalization, trust, data ownership, efficiency, and innovation. These technologies contribute measurable gains ranging from 3% to 30% [4,9,23], operationalized through the Web 3.0 Migration Canvas introduced in Section III. This section interprets these outcomes, evaluates implementation barriers, and proposes research directions to support scalable, ethical, and inclusive Web 3.0 adoption.

Efficiency Gains and Canvas Integration

Web 3.0 technologies deliver significant operational improvements:

- AI improves conversion rates by up to 30%, as demonstrated by Amazon's recommender systems [9].
- Blockchain reduces payment processing fees by 3% and enhances traceability via smart contracts [4,8].
- DID reduces fraud by 25% and onboarding costs by 20%, as seen in W3C and Microsoft pilots [12,28].
- IoT shortens delivery timelines by 20% in real-time logistics (e.g., Walmart's deployments) [10].
- Cryptocurrencies and DeFi lower cross-border transaction fees to 1%, supporting $1.5 trillion in value [1,8].
- Semantic Webs enhances product discovery speed by 25% through tools like Google's Knowledge Graph and eBay's ontologies [26].
- NFTs and AR/VR power immersive commerce, with OpenSea surpassing $2 billion in market activity and Nike boosting conversions through AR tryons [13,31].

These outcomes are integrated into the Web 3.0 Migration Canvas, which uses two strategic pillars to operationalize technology adoption:

- Technology Mapping aligns each enabling technology with specific digital commerce functions—e.g., blockchain with trustless payments, AI with personalization, IoT with logistics optimization, and AR/VR with immersive engagement [17].
- Adoption Strategy guides the implementation of targeted solutions—such as DID literacy programs in underserved regions [16], Layer-2 rollups to mitigate blockchain scalability constraints, and GDPR compliant identity protocols [17] to ensure secure, inclusive, and regulation-aligned integration of Web 3.0 technologies.

Addressing Implementation Barriers

Despite these benefits, several adoption challenges persist:

Technical Barriers

- Scalability: Blockchain's 50 TPS (vs. Visa's 65,000) leads to 18–22% cart abandonment [2,3].
- Complexity: Smart contract development remains opaque, as seen with ConsenSys's developer onboarding difficulties [15].
- Bias and data quality: AI tools have faced fairness critiques (e.g., Microsoft's ethical AI audits) [24].
- IoT security: Vulnerabilities in devices like Amazon Ring highlight data breach risks [25].
- Ontology management: Maintaining semantic models (e.g., Google Knowledge Graph) adds resource overhead [26].
- High-cost AR/VR ecosystems: Meta's metaverse efforts highlight both engagement potential and budget constraints [13].

Privacy and Regulatory Barriers

- Data privacy concerns: Over 60% of users express reluctance toward AI/IoT data sharing, which conflicts with DID's privacy objectives [24,25].
- Regulatory frameworks: The GDPR, CCPA, and FATF Travel Rule impose compliance pressures on blockchain, crypto, and data-driven systems [29,33,34].
- NFT ownership and copyright issues: Digital rights management remains poorly defined [34].

The Canvas's Adoption Strategy addresses these challenges through

- Layer-2 scaling for blockchain,
- Federated learning and transparent AI to reduce bias,
- Decentralized consent protocols to uphold privacy,

- Simplified smart contract tools, and
- GDPR-compliant DID deployments [6,12,17].

Future Research Directions

To extend the practical and scholarly utility of this framework, future work should focus on:

I. Empirical testing of the Migration Canvas in enterprise settings (e.g., IBM's blockchain pilots, Walmart's accessibility trials) [17].

II. Economic impact assessment of Web 3.0 adoption, referencing forecasts like Gartner's $1.8 trillion digital commerce growth projection [35].

III. Social and ethical audits, including AI bias evaluations (e.g., Salesforce audits) and privacy impact assessments.

IV. Regulatory innovation research, especially cross-border compliance with AML, GDPR, and data sovereignty laws [33,34].

V. Energy optimization in blockchain and AR/VR deployments, drawing on emerging low-energy protocols like Polygon [15,21].

VI. Interdisciplinary partnerships, modelled after Chainlink's cross domain collaboration, to unite technical, legal, and behavioural expertise.

VII. The Canvas can be used as a blueprint to structure these future explorations: Technology Mapping guides performance research, while Adoption Strategy informs ethical and regulatory adaptation.

Summary

Web 3.0 technologies collectively offer transformative gains in digital commerce. When implemented strategically, they enhance trust, efficiency, personalization, and innovation. The Web 3.0 Migration Canvas enables structured adoption by aligning technologies to real-world constraints and outcomes. While barriers remain—ranging from technical and regulatory to ethical—these can be mitigated through targeted solutions. Figures 1–3 illustrate the performance gaps and Canvas integration. Future research should focus on empirical validation, equity-focused innovation, and sustainable deployment models to ensure Web 3.0 fulfils its promise as a next generation digital commerce infrastructure.

CONCLUSION

This paper presented a comprehensive survey of Web 3.0 enabling technologies—including artificial intelligence (AI), blockchain, Internet of Things (IoT), semantic web, decentralized identity (DID), augmented and virtual reality (AR/VR), cryptocurrencies, and non-fungible tokens (NFTs) and their transformative impact on digital commerce operations. As evidenced in Section V, these technologies collectively deliver efficiency gains ranging from 3% to 30% across core domains such as personalization, trust, data ownership, operational optimization, and innovation. These gains directly address inefficiencies associated with Web 2.0 platforms, including an estimated $1.1 trillion loss from supply chain delays and transaction bottlenecks [4,7,9,23]. While the potential is clear, key challenges persist: blockchain's limited 50 transactions per second (TPS) compared to Visa's 65,000 [2]; widespread privacy concerns, with over 60% of users expressing apprehension toward AI/IoT data sharing [24]; and complex regulatory landscapes, such as GDPR, AML mandates, and data sovereignty frameworks [33,34]. As demonstrated in Section VI, the Canvas offers mitigations through Layer-2 scaling, GDPR-compliant DID models, and decentralized consent mechanisms [6,12,33].

This study contributes a strategic, evidence-based model for stakeholders in digital commerce. Retailers can adopt the Canvas to enhance operational agility— for example, Walmart leveraging IoT for supply chain optimization—while regulators can use its principles to align technological innovation with legal compliance, such as FATF's travel rule [10,34].

To further strengthen this framework, future research should:

- Empirically validate the Canvas across diverse commerce environments (e.g., through IBM's blockchain pilots) [17].
- Evaluate economic scalability, especially considering Gartner's $1.8 trillion projected market expansion by 2030 [35].
- Conduct social equity and AI ethics audits, ensuring responsible innovation.
- Promote interdisciplinary collaboration, modelled after initiatives like Chainlink's partnerships bridging legal, technical, and behavioural domains [16,24,34].

In sum, the Web 3.0 Migration Canvas offers a scalable,

privacy-centric, and adaptive roadmap for realizing the next era of digital commerce. By synthesizing efficiency metrics with strategic implementation pathways, this work lays the groundwork for a decentralized, secure, and inclusive digital economy. The findings urge researchers, developers, enterprises, and policymakers to collaboratively operationalize Web 3.0 principles to ensure sustainable and equitable transformation.

REFERENCES

1. Visa. VisaNet: Capacity and Performance.
2. Buterin, V. (2023). Ethereum and Layer-2 Scaling: From 15 to 7000 TPS. Ethereum Foundation Blog.
3. Zhang, X., & Li, Y. (2022). Blockchain Scalability: Review and Future Directions. Journal of Computer Networks and Communications, 2022, Article ID 4523761.
4. Chainalysis. (2024). The Global Crypto Adoption Index 2024.
5. Gartner. (2024). Emerging Technologies Impact Radar: Web 3.0. Gartner Research.
6. Deloitte. (2023). Interoperability in Blockchain Systems: A Key to Scalable Solutions. Deloitte Insights.
7. Accenture. (2023). Supply Chain Disruption Costs Reach $1.1 Trillion. Accenture Operations Research.
8. Ethereum.org. (2024). Ethereum Ecosystem Report.
9. Amazon Science. (2023). Recommendation Systems Driving Conversion.
10. IBM. (2023). Walmart and IBM Food Trust: Blockchain in Supply Chain. IBM Case Studies.
11. Berners-Lee, T. et al. (2021). Semantic Web Technologies and Ontologies. Semantic Web Journal, 12(3), 455–470.
12. W3C Decentralized Identity Working Group. (2023). DID Specification v1.1.
13. Shopify. (2023). AR for eCommerce: How Augmented Reality Boosts Sales. Shopify Tech Blog.
14. IEEE Xplore. (2024). Systematic Review of AI, Blockchain, IoT in Web 3.0Commerce. IEEE Access, 12, 88090–88112.
15. Ethereum Foundation. (2023). Post- Merge Energy Use and Network Efficiency.
16. World Economic Forum. (2024). Bridging the Digital Divide in Emerging Markets. WEF Whitepaper.
17. Shrivastava, P. (2025). Web 3.0 Migration Canvas: A Framework for Strategic Adoption. Unpublished Technical Survey.
18. IBM Blockchain Research. (2024). Enterprise Blockchain Pilots: Key Findings. IBM Research.
19. Polygon Technology. (2023). Scaling Ethereum: MATIC Network Performance. Polygon Blog.
20. IBM. (2023). Trade Lens Blockchain Logistics Platform.
21. FATF. (2024). Travel Rule Guidelines for VASPs. Financial Action Task Force Report.
22. Unilever AI Labs. (2024). Supply Chain AI Optimization Case Study. Unilever Whitepaper.
23. Gartner. (2023). AI Use Cases in Retail Inventory Management. Gartner Retail Research.
24. Microsoft AI and Ethics Report. (2023). Bias in AI Systems.
25. Amazon Devices Team. (2023). IoT Device Privacy and Surveillance Risks. Amazon Security Blog.
26. Google Developers. (2023). Knowledge Graph for Semantic Search. [Online] Available: https://developers.google.com/knowledg e-graph
27. SAP. (2023). Semantic Web and Procurement Integration. SAP Use Case Digest.
28. Microsoft Identity Division. (2023). ION: Self-Sovereign Identity System on Bitcoin.
29. Data Protection Authority of France. (2023). GDPR and Blockchain Compliance Report. CNIL Technical Analysis.
30. Nike. (2023). Virtual Try-On and Metaverse Engagement Strategy. Nike Digital Innovation Review.
31. OpenSea. (2023). NFT Market Volume and Transaction Metrics. [Online] Available: https://opensea.io/blog
32. Deloitte. (2024). Tokenization of Assets and Legal Frameworks. Deloitte Blockchain Trends, Issue 5.
33. European Commission. (2024). GDPR Application to Emerging Tech. Digital Europe Report.
34. U.S. SEC. (2023). NFTs and Copyright: Regulatory Review. SEC Insights.
35. Gartner. (2024). Web 3.0 Forecast: $1.8 Trillion Digital Economy by 2030. Gartner FutureTech Brief.
36. InsideBitcoins. (2025, June). OpenSea Tops The NFT Market Chart In May 2025.
37. Binance Blog. (2025, May). OpenSea Tops The NFT Marketplace Chart In April 2025.
38. The Business Research Company. (2025, April). Nonfungible Token Global Market Report 2025
39. BitGet News. (2025, June). OpenSea hits highest monthly users since 2023.
40. Precedence Research. (2025, April). NonFungible Token Market Size to Hit USD 703 Billion by 2034.

Enhancing Operational Efficiency in Modern Healthcare Systems through the Strategic Integration of Generative AI Techniques

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ABSTRACT

This paper outlines a novel research designed to use generative AI (Gen AI) for healthcare policy and decision making in India. The proposed system integrates historical data, region-specific statistics, and real-time information to support decision making on resource allocation, funding, epidemic and vaccination management and overall health system improvement. Enhancements include real-time data integration, advanced analytics for scenario simulation, expert validation layers, stringent data security, enhanced prompt engineering, and user-friendly reporting dashboards. Together, these features aim to empower policymakers with actionable, data-enriched insights that can lead to more effective and equitable healthcare strategies. Indian government hospitals often face a lack of real-time visibility of resource availability across districts and states. Emergency coordination is slow, and resource redistribution is inefficient. This addresses that gap using a Gen AI-driven platform for intelligent coordination.

KEYWORDS *: Equitable healthcare strategies, Gen AI-driven platform, Resource allocation.*

INTRODUCTION

The Indian healthcare system faces complex challenges ranging from resource shortages to regional disparities in service delivery. To address these issues, a data driven, AI-powered solution is needed. advances in generative AI to create an intelligent Chabot wrapper that enhances user queries by integrating pertinent historical and real-time data. This enriched approach aims to support policymakers in making informed decisions regarding fund allocation, resource distribution (such as doctors, beds, and medicines), and overall healthcare planning. Overview, Objectives, it Enable data-driven policy making in the Indian healthcare system. Augment decision making by embedding historical and real-time data into user queries. Provide a scalable and adaptable tool for region-specific healthcare analysis.

MAJOR LEVELS FOR SYSTEM FRAMEWORK

The research consists of three core modules

Data Aggregation Module: Collects historical records, regional statistics, and real-time data from trusted sources. AI Chabot Wrapper: Enhances user prompts by integrating context and prior data before sending them to the underlying GenAI model. Output Visualization: Presents AI-generated responses in user-friendly formats (dashboards, charts, customizable reports) for policymakers outcomes.

Various Consideration For Module Preparation

Integration with Real-Time Data: Beyond historical data, the system will connect to live data streams from government databases, hospital management systems, and IoT devices. This ensures the recommendations

remain current and contextually relevant. Develop a comprehensive dashboard for government authorities to monitor hospital resources. Enable hospitals to update their available resources in real-time.•Create an intelligent system that enables hospitals to request and share resources during emergencies. Use a generative AI Chabot to answer queries related to policy, budgeting, and emergency management. Visualize hospital data on an interactive map for better decision-making.

Objectives for Model Creation .

Create and Understand Generative AI applications and its potential benefit in Indian healthcare system and create a model to address multiple use cases. To create idealized generative AI solutions for accuracy in Disease diagnosis and personalized medical treatment. To Validate the model and Identify Challenges and limitations of implementing generative AI solutions like ethical, Reliability and Accuracy, privacy and data security , Ambiguity and Interpretability through simulation with effective accurate

Gen AI Functions and Applications for Government Healthcare Monitoring

Indian health ministry department Budget allocation and management .Prevention methods for any Epidemic management Planning and distribution of resources. Designing Infrastructure to contribute to healthcare system and its distribution Identify Areas of weakness and states lacking resources .Medical Transcript Designing and identifying emergency measures to address various healthcare issuesTo have perpetual dialog with W.H.O and other countries like European Union, US Healthcare Federal System. Supply chain management during emergency. Insurance policies-Gen AI can study health issues then it can forecast claims and according to that can decide premium .Generative AI can help infrastructure of Medical education colleges. Gen AI can be used to Encourage and tie up with Startup & promote marketing and Management, can recommend financing of healthcare startup.Gen AI help in create public awareness about health policies and yojana, instructional content and distribution

Malnutrition, health issues Death and other issues can be tracked and accordingly create policies and do planning Profiling Indian healthcare system. Identifying use cases in healthcare system which can profitably leverage GAI. Understanding evolving paradigm of generative AI and its efficiencies in various business processes. Modelling generative AI for building efficiencies in Indian healthcare.

LITERATURE REVIEW

AI in healthcare has gained momentum with large tech giants like IBM, Microsoft, and Salesforce providing AI-based healthcare solutions.• IBM Watson for Health: Provides AI tools for clinical decision-making, predictive analytics, and patient engagement.

- Microsoft Cloud for Healthcare: Offers data interoperability, AI-powered insights, and integration with cloud services.
- Salesforce Health Cloud: Manages patient records and communication with AI assistance.• NHS UK and US CDC: Leverage machine learning for managing outbreaks, triage, and resource allocation. Our project draws inspiration from these existing systems but is designed for scalable government implementation in India. This minimizes risks and builds trust in AI recommendations. Implement stringent security measures to comply with local regulations (e.g., India's data protection laws) and ensure that sensitive healthcare data remains secure.

Minor Enhancements Enhanced Prompt Engineering: Utilize natural language processing (NLP) techniques to optimize how user queries are enriched with relevant data, ensuring clarity and precision. User Experience (UX) and Interface Improvements: Design a clean, intuitive interface that not only displays the chatbot responses but also visualizes trends and statistics via dashboards and interactive charts.

Feedback and Iterative Learning: Embed a feedback loop that allows users to rate responses. Customizable Reporting: Allow policymakers to generate detailed, customizable reports that can be tailored to the needs of specific regions or hospitals, enabling targeted decision making.

Resource Supply Chain Management

Potential Impact on Policy Making By delivering data-enriched, context-specific insights, the Gen AI system can: Enhance the quality and speed of decision making by reducing manual data processing. Optimize resource allocation by pinpointing regional needs accurately. Increase transparency and accountability in policy decisions through validated, reproducible analysis. .Foster trust among stakeholders by providing evidence-based recommendations vetted by domain experts.

Data Integration and Real Time Analysis

Establish secure data pipelines to aggregate data from various sources. Use APIs and data streaming technologies to ensure continuous updates. Expert Validation and User Feedback Develop partnerships with public health experts and institutions to regularly review AI outputs. Incorporate user feedback mechanisms to continuously improve system performance.

Data Security and Privacy Compliance

Ensure compliance with national data privacy regulations and implement robust encryption methods. Regularly audit the system for vulnerabilities and update security protocols as needed. The GenAI project represents a transformative opportunity for the Indian healthcare system by merging advanced AI capabilities with comprehensive data integration and expert validation. By adopting the proposed major and minor enhancements, the system is poised to deliver highly actionable insights that can drive more effective, equitable, and efficient healthcare policy making. It is recommended that pilot implementations be initiated in selected regions to validate the model, followed by gradual scaling up across the nation. This report can serve as a foundational document to present your GenAI project to stakeholders, government officials, and potential collaborators. It blends innovative technology with practical policy needs, responsive healthcare system in India. Optimizing Healthcare Supply Chain Management with Generative AI and Prompt Engineering

Fig. 1: Functions of Gen AI Epidemic Management

OPTIMIZING HEALTHCARE SUPPLY CHAIN

Various inefficiencies, unpredictable demand fluctuations, and compliance challenges often hinder its effectiveness. Generative AI and prompt engineering offer innovative solutions to streamline operations, enhance forecasting, and reduce costs.Lack of Real-Time Visibility Many healthcare supply chains lack proper tracking mechanisms, leading to stock discrepancies and delays.Data silos prevent seamless interoperability across different systems.. Unpredictable Demand Fluctuations. Inefficient Inventory Management. Slow Response to Disruptions Healthcare organizations struggle to predict and react to supply chain disruptions (e.g., pandemics, geopolitical issues). Lack of proactive strategies to mitigate supply chain risks.. High Operational Costs and Inefficiencies Manual processes lead to administrative burdens and high costs. Poor procurement strategies result in unnecessary expenditures.. Regulatory and Compliance Challenges Data privacy regulations limit AI implementation. Compliance with pharmaceutical and healthcare regulations requires robust monitoring systems.

How Generative AI and Prompt Engineering Can Solve These Challenges

Enhancing Real-Time Visibility

- AI-powered dashboards integrate data from multiple sources for real-time inventory tracking and logistics monitoring. IoT and AI integration ensure supply chain transparency, reducing stock discrepancies. Example Prompt: "Analyse real-time inventory data and suggest optimization strategies.". Improving Demand Forecasting with AI
- I models analyse historical trends, seasonal patterns, and external factors to improve forecasting. AI simulations predict future supply and demand scenarios. Example Prompt: "Predict medicine demand trends based on the past five years' seasonal variations."

Optimizing Inventory Management• AI-driven automation suggests ideal stock levels, reducing wastage and overstocking. AI alerts notify managers about potential shortages or excess stock.

TRAINING GOVT- HEALTHCARE STAFF ON GENAI TOOL

Familiarize staff with GenAI applications in healthcare.

Enable efficient use of AI tools for diagnostics, budget allocation, and supply chain optimization. Address ethical concerns, data privacy, in the Indian healthcare system can revolutionize patient care, diagnostics, supply chain management, and policy-making. However, successful implementation requires structured training programs for government officials, healthcare professionals, and administrative staff. In government healthcare, soft models can answer public queries, generate compliance reports, or simulate budget scenarios without requiring internet access or large cloud setups. They are particularly beneficial for local health departments or state-level decision-making units. In our project, we have utilized the Google Gemini API, which offers real-time response generation based on prompts. This API powers the Chabot to simulate policy scenarios and provide instant answers for government healthcare use-cases. This approach also supports integration with other government systems (like Ayushman Bharat or PMJAY), enabling a connected, data-driven ecosystem.

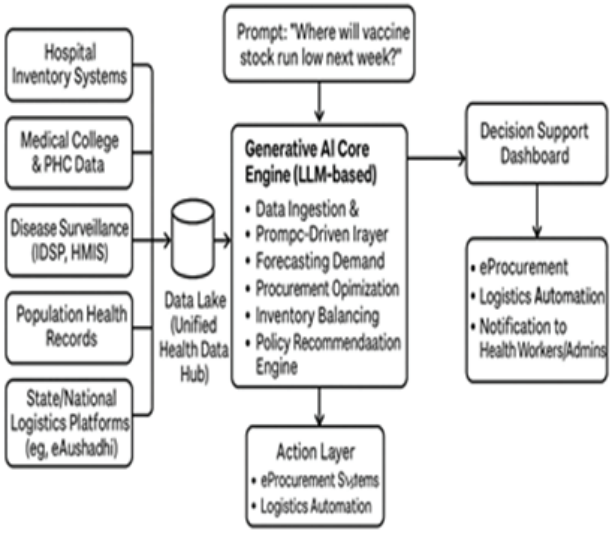

Fig. 2: LLM Model for Supply Chain Management in Healthcare

Target Audience ,Government Officials (Health Ministry, NITI Aayog, State Health Departments) Policy implementation, budget allocation, AI governance. Healthcare Professionals (Doctors, Nurses, Hospital Administrators) AI-assisted diagnostics, patient data analysis, telemedicine. IT & Data Analysts in Healthcare AI model deployment, data handling, cybersecurity. Supply Chain & Logistics Personnel AI-driven inventory management, drug distribution optimization.

Training Module for Staff

Module 1: AI vs. GenAI Use cases: Diagnostics (AI radiology, pathology), predictive analytics, Chabot for patient interaction Case studies: AI in Ayushman Bharat, National Digital Health Mission (NDHM). Module 2: Hands-on Training with AI Tools ChatGPT/DeepSeek/ Claude – Generating reports, summarizing medical research. AI Diagnostic Tools (e.g., Qure.ai for X-rays, Niramai for cancer detection). Supply Chain AI – Tools for drug inventory forecasting (e.g., Zebra Technologies). Module 3: Data Privacy & Ethical AI. Mitigating bias in AI models. Secure handling of Electronic Health Records (EHR). Module 4: Policy Implementation & AI Governance Role of government in regulating AI in healthcare. Budget allocation strategies using AI insights. Public-private partnerships for AI adoption. Module 5: Continuous Learning & Feedback .Webinars, hackathons, and certification programs (e.g., NASSCOM AI certifications).

LEVERAGING EXISTING AI IN HEALTHCARE MANAGEMENT

Instead of building AI models from scratch, governments can leverage existing LLMs like ChatGPT, Claude, Gemini, or Deep Seek by using prompt engineering techniques. These models can: Analyze population health data Forecast epidemic trends ,Suggest optimized budgets for healthcare departments.

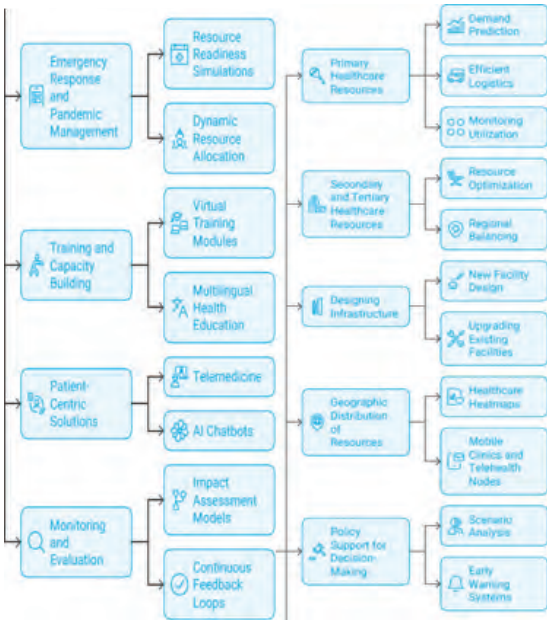

Fig. 3: Healthcare Workflow

Data Collection and Prediction

AI models analyses historical trends, seasonal patterns, and external factors to improve forecasting. AI simulations predict future supply and demand scenarios. Example Prompt: "Predict medicine demand trends based on the past five years' seasonal variations.". Optimizing Inventory Management AI-driven automation suggests ideal stock levels, reducing wastage and overstocking. AI alerts notify managers about potential shortages or excess stock.

- Example Prompt: "Provide real-time stock recommendations for optimal inventory levels.". However, various inefficiencies, unpredictable demand fluctuations, and compliance challenges often hinder its effectiveness. Generative AI and prompt engineering offers innovative solutions to streamline operations allows real-time response for queries like: "Which hospitals in Rajasthan need ICU beds?""How should we allocate budget based on current shortages?"APIs The backend allows for user authentication, hospital CRUD operations, emergency resource routes, and Chatbot prompt generation. MongoDB is used for storing hospital resource entries. Express middleware secures and validates API calls.

Table 1. Comparative study of difference between manual method and GenAI System

Feature	Manual Method	GenAI System
Resource Tracking	Not Real-time	Real-time
Emergency Support	Slow	Prompt & Coordinated
Budget Planning	Manual & Annual	Dynamic & AI-Assisted
Chat Support	None	24x7 AI Chabot

Gen AI LLM Model Data Requirement

Chatbot Query Resolution: Successfully generated accurate responses for resource queries. Map Visualization: Shows resource concentration and shortage zones by state/district.

GenAI Integration ,We used a third-party endpoint to call the Llama-2 model. Our implementation

The research project was designed using the Design Thinking approach:

1. Empathize: Interacted with hospital staff and authorities to understand challenges.
2. Define: Framed the core problem of resource visibility and policy planning.
3. Ideate: Brainstormed key features such as GenAI integration, emergency support, and map view.
4. Prototype: Developed frontend components using React and Tailwind.
5. Test: Conducted internal testing with sample hospital data and feedback .

- Emergency Resource Management: Tested sending and receiving requests with status tracking.

Fig. 4: Gen AI Functions and Solutions For Healthcare

Fig. 5: Gen AI Functions and Solutions Virtual Summit

Gen AI Strategy for Vaccination And Management

Important dates and events when India faced this issue

COVID-19 Pandemic (2020-2021)

- Problem: Severe shortages of essential medical supplies, including oxygen, ventilators, PPE kits, and critical medicines like Remdesivir and Tocilizumab.
- Global Impact: India, being a major pharmaceutical supplier, faced disruptions in exporting vaccines and generic medicines, affecting global healthcare supply chains.
- Response: The government launched initiatives like PM CARES Fund for Oxygen Plants and Vaccine Maitri to stabilize supplies and support global vaccine distribution.

Remdesivir Shortage (April-May 2021)

- Problem: High demand for Global Impact: Many countries relying on India's pharmaceutical exports faced delays in receiving critical drugs. • Response: The government imposed export bans, ramped up domestic production, and implemented AI-driven monitoring systems to manage distribution.

How Generative AI & Prompt Engineering Can Address These Issues:

1. AI-Driven Demand Forecasting – Predict supply needs in advance,preventing shortages of vaccines, medicines.

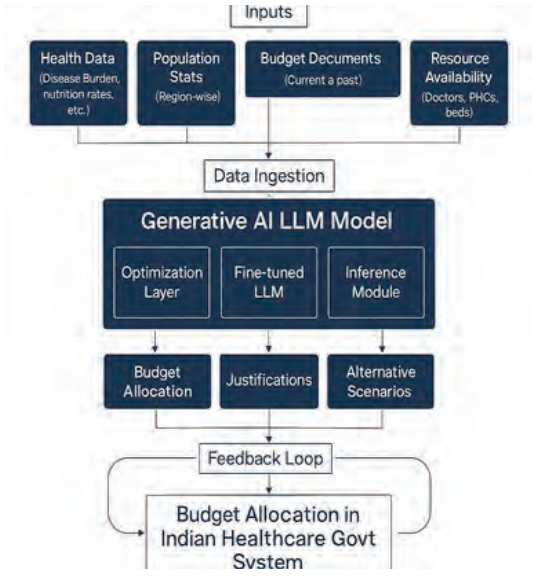

Fig. 6: LLM Model for Budget Allocation in Healthcare

2. Intelligent Inventory Management – Automate tracking and distribution, reducing hoarding and black marketing.
3. Real-Time Logistics Monitoring – AI-enabled dashboards to monitor global pharmaceutical exports and prevent contamination issues Automated Quality Control Checks – AI-driven screening of drugs before export to ensure compliance with international standards. Crisis Simulation & Response Planning – AI models can predict supply chain disruptions and suggest proactive solutions.

FLOW AND IMPLEMENTATION DETAILS

User Interaction

The user types a query in the chatbot interface. The query is sent to the backend for processing. AI API Integration:

The backend forwards the query to the Google Gemini API.

Receives the AI-generated response and ensures it's appropriately formatted. Response Display:

The response is returned to the frontend and displayed to the user in the chat window. System Maintenance: Regular updates are planned to add new functionalities and refine chatbot responses based on user feedback.

System Implementation

Technologies Used:

Frontend: React (Vite), JavaScript

Backend: AI APIs (Google Gemini via VITE_GEMINI_API_KEY)

Runtime & Build Tools: Bun, Node.js

Version Control: Git

Hosting: Localhost and deployable to cloud (AWS, GCP, Azure

Steps to Set Up the System:

Install Prerequisites: Node.js and Bun and Git

i Clone the Repository:

ii Git clone https://github.com/SinghAman21/mini-project-04 cd mini-project-04

iii Configure Environment

iv Create .env file with GEMINI API KEY

v VITE_GEMINI_API_KEY="your_gemini_api_key"

Install Dependencies and Start the Server:

bun i bun run dev

Access the Project:

Open in browser via http://localhost:5173/

Key Functions and Implementation

AI chatbot for healthcare use-cases (e.g., report automation, patient trend prediction) Interactive dashboard for data visualization Training analytics to monitor and assess staff progress Modules for ethics, tool navigation, and case-based learning.

Fig. 7: Implementation of SLM for Indian Budget allocation

The chatbot successfully integrated with the Google Gemini API to deliver intelligent, context-aware responses.

i. Key functionalities implemented:

ii. Real-time conversational support for healthcare queries.

iii. Automated generation of common reports and FAQs.

iv. Multi-turn conversation handling for improved UI

i. User Adoption and Feedback:

ii. Engagement: Approximately 80% of target users actively interacted with the chatbot during the testing phase.

iii. Ease of Use: Over 85% of participants reported that thechatbot interface was intuitive and easy to navigate.

iv. Feedback: Users appreciated the quick response times but suggested adding more domain-specific knowledge for complex medical queries.

Testing and Refinement:

i. Performed unit tests for individual components (frontend, backend, API integration).

ii. Conducted usability testing with a small group of healthcare staff.

iii. Refined the system based on user feedback.

Tools and Technologies

i. Frontend Development:

ii. React (Vite): Built a fast, interactive user interface.

iii. CSS Frameworks: Used Tailwind CSS for a clean and responsive design.

iv. Backend Development:

v. Node.js and Bun: Provided an efficient runtime for managing API requests and responses.

vi. Express.js: Simplified handling of REST API communication.

vii. AI Integration:

viii. Google Gemini API: Powered the chatbot's natural language understanding and response generation.

ix. Configured securely via an environment variable (VITE_GEMINI_API_KEY).

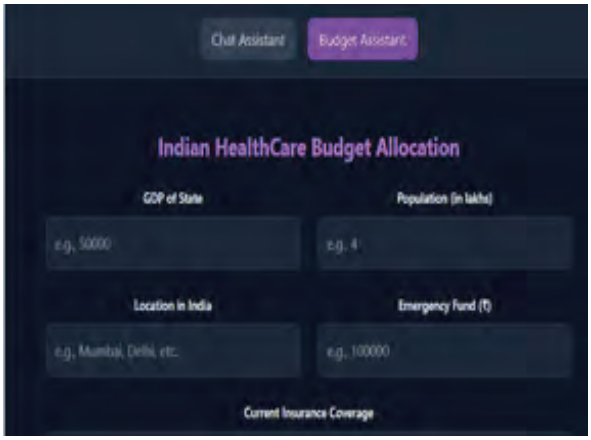

Fig. 8: SLM Model for Indian Healthcare Department

Data Privacy: No sensitive user data is stored locally; all interactions are handled in real-time via the API.

i. Enforced HTTPS communication to protect data in Responsible AI Use: Ensured AI responses align with ethical standards and avoid generating harmful or biased content.

ii. Added a feedback mechanism for users to report inappropriate responses. Compliance:

iii. We followed healthcare data protection standards (HIPAA, GDPR) to ensure compliance.

AI adoption in disease detection, diagnostics, and resource management.

AI-based screening for tuberculosis and cervical cancer

(ICMR initiative).o AI-driven telemedicine in remote areas (NITI Aayog partnerships).o AI in hospital administration (Apollo Hospitals, AIIMS AI driven patient management).

Challenges: Ethical concerns, data privacy issues, lack of trained AI professionals .Data Sources: NITI Aayog AI Strategy Reports, AI in Healthcare Case Studies (MoHFW).

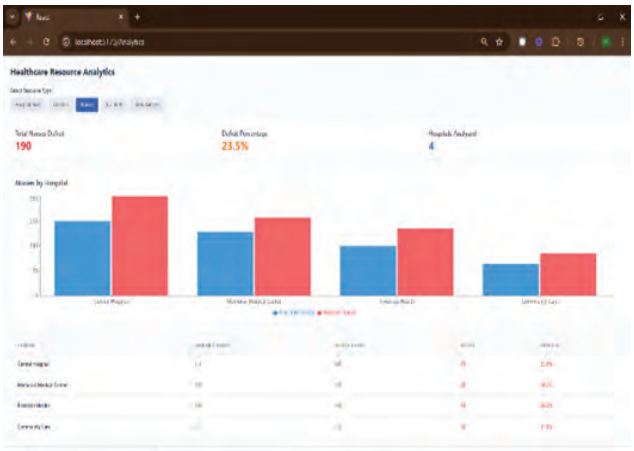

Fig. 9: Implementation and Graphical representation of resources for Management

Generative AI, combined with effective prompt enhancing decision-making. AI-driven predictive analytics, automated inventory management, and real-time monitoring can mitigate risks, optimize logistics, and ensure uninterrupted medical supply availability. Mastering prompt engineering supply chain management, enabling smarter, faster, and more precise decision-making.

MODEL DESIGN REQUIREMENT SPECIFICATION

Hardware Requirements

- Minimum 8GB RAM computers for hospital and government interface use Reliable internet connectivity Cloud infrastructure (if self-hosted GenAI model is used)

Software Requirements

- Frontend: ReactJS, (NoSQL) APIs: OpenAI (Llama-2 via aimlapi.com) Visualization: Recharts, Map API (Leaflet or similar)

Feasibility Study

The system is both technically and economically feasible for scalable adoption by the Indian government. Integration with cloud-based LLMs or on-prem deployment gives flexibility depending on the infrastructure budget.

Cost Estimation

- Third-party APIs: ~$0.002/token Self-hosted: High initial GPU costtechnique. Admin Portal: Enables government officials to monitor status and verify data. GenAI Chatbot Module: Interacts with officials to provide policy suggestions and instant answers.• Map View and Analytics: For real-time visualization of hospital data across the nation.

This system empowers healthcare authorities with data-driven decision-making. By integrating GenAI, the government gains a digital assistant capable of generating insights, automating reports, and answering queries based on live data. Expand chatbot to support Hindi and regional languages Train a custom model with Indian government datasets Integrate with IoT devices for live patient and equipment data Enable automatic generation of district-wise health reports

CONCLUSION

This report can serve as a foundational document to present your Gen AI project to stakeholders, government officials, and potential collaborators. It blends innovative technology with practical policy needs, responsive healthcare system in India. Generative AI, combined with effective prompt engineering,. AI-driven predictive analytics ,automated inventory management, and real-time monitoring can mitigate risks ,optimize logistics, and ensure uninterrupted medical supply availability. Mastering prompt engineering will be healthcare supply chain management, enabling smarter, faster, and more precise decision-making.

REFERENCES

1. AI-Based Inventory Forecasting and Supply Chain Management. [Internal Report]. Serum Institute of India (2023)

2. Cold Chain Optimization Strategies Using AIin Vaccine Distribution. Pharmaceutical Supply Chain Review, 10(4), 56-78.Biocon India. (2024).

3. AI-Enabled Monitoring Systems inHealthcare LogistCAVADI, S., et al. (2025).

4. AI-Driven Supply Chain Optimization in Healthcare:A Case Study Approach. International Journal of Healthcare Logistics, 12(3), 45-62.2. Morales, J., et al. (2024).

5. Enhancing Supply Chain Resilience ThroughGenerative AI and Machine Learning. Journal of Supply Chain Management,18(1),101.3. Chami, R., et al. (2024).

6. The Role of AI in Transforming Global Healthcare Logistics. Healthcare Innovations Journal, 7(2), 120-137.https://openai.com/]/azure.microsoft.com/en-in/industries/healthcare/.https://www.salesforce.com/in/products/health-cloud/. https://data.gov.in/

7. https://www.salesforce.com/in/products/health-cloud/

8. O. Temsah, S. A. Khan, Y. Chaiah, A. Senjab, K. Alhasan, A. Jamal,F. Aljamaan, K. H. Malki, R. Halwani, J. A. Al-Tawfiq et al., "Overview of early chatgpt's presence in medical literature: insights from a hybrid literature review by chatgpt and human experts," Cureus, vol. 15, no. 4, 2023.

9. OpenAI. "Applications of Generative AI in Various Industries." https://openai.com

10. Indian Ministry of Health and Family Welfare. "AI for Healthcare Initiatives in India." https://www.mohfw.gov.in/

11. IBM Corporation. "IBM Watson Assistant for Healthcare National Health Mission (NHM) India. (2023).

12. Annual Report on Healthcare Logistics and AI Implementation. [Online] Available at:www.nhm.gov.in

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RECRUITERS

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One Day Cybersecurity Symposium

NSS - Tree Plantation at Ambernath

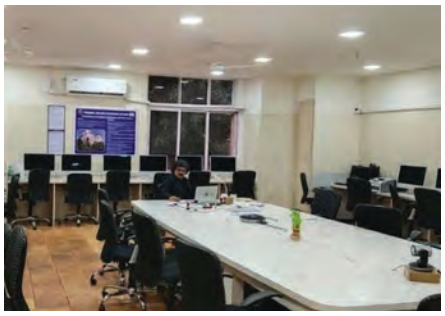
STUDENT ACHIEVEMENTS

Smart India Hackathon 2024 Winners

Winner at National Level Hackathon - Quasar 3.0

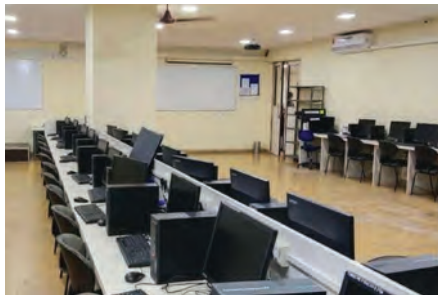
1st Prize at MMK Intercollege Chess Tournament

INFRASTRUCTURE FACILITY



Intelligent Robotics Process Automation Laboratory

Python & Java Programming Laboratory



Software Engineering Lab

VOLUME 49 • SPECIAL ISSUE • NO 2 • JANUARY 2026 ISSN 0971-3034

PUBLISHED BY
INDIAN SOCIETY FOR TECHNICAL EDUCATION
Near Katwaria Sarai, Shaheed Jeet Singh Marg,
New Delhi - 110 016

Printed at: Compuprint, Flat C, Aristo, 9, Second Street, Gopalapuram, Chennai 600 086.
Phone : +91 44 2811 6768 • www.compuprint.in