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TABLE OF CONTENTS

Contents

River Journal, 1.

Integrating Convolutional Neural Networks and Meta LLaMA2 for Recipe Generation from Ingredient Lists and Images

Aparna R. Sawant, Soham R. Karandikar, Prasad A. Kamble, Kshitij S. Kalrao, Parth V. Kallurwar, Jaee R. Kale

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Abstract

This paper proposes a system that integrates Convolutional Neural Networks (CNNs) and the Meta LLaMA2 language model to generate structured recipes from either textual ingredient lists or food images. CNNs identify ingredients from images, while the fine-tuned LLaMA2 model (trained on the RecipeNLG dataset) generates coherent recipes. A real-time, interactive interface is built using Streamlit and Flask in a client-server setup. Evaluation using BLEU and ROUGE-L metrics validates the model's effectiveness. The work contributes to intelligent and personalised recipe recommendation systems with real-world applicability.

Keywords: recipe generation, CNN, Meta LLaMA2, image classification, language models.

1 Introduction

Technological advancements have reshaped everyday life, including cooking practices [1]. With the popularity of online recipe platforms, there is increasing interest in systems that can generate recipes using AI and available ingredients [2]. This study explores the integration of Convolutional Neural Networks (CNNs) and the Meta LLaMA2 language model to develop a sys-

River Journal, 1–10.

tem that generates recipes from either a list of ingredients or corresponding images. CNNs handle image-based ingredient recognition, while LLaMA2 excels in contextual natural language generation [3, 4]. The system aims to enhance culinary accessibility, encourage creativity, and enable personalised meal preparation. It transforms conventional kitchens into spaces of intelligent automation and gastronomic exploration.

2 Related Work

Significant advancements have been made in ingredient recognition and recipe generation using Convolutional Neural Networks (CNNs) and large language models (LLMs). Touvron et al. [5] introduced Meta LLaMA2, which was made publicly accessible via Huggingface [6], facilitating model fine-tuning and deployment. Practical strategies for adapting LLMs using the Transformers and Datasets libraries have been discussed in [7, 8]. RecipeNLG [9], derived from Recipe1M+ [10], serves as a foundational dataset in culinary text generation. In the domain of ingredient recognition, Rodrigues et al. [11] and Morol et al. [12] proposed CNN-based systems using datasets such as Fruits and Vegetables Recognition. Transfer learning techniques, including VGG and MobileNet, have been applied to fruit classification and quality detection in [13], consistently achieving robust results. These studies collectively motivate the integration of CNNs for image-based recognition and LLMs for recipe generation in the proposed system.

3 Proposed Methodology

3.1 Block Diagram

The high-level architecture of the proposed system is shown in Figure 1. It is structured into two primary components: the client and the server. The client includes the user interface and a lightweight Convolutional Neural Network (CNN) for ingredient recognition. The server, hosted on Google Colaboratory using Flask and accessed via Ngrok, runs the Meta LLaMA2-based recipe generation model. Users can either input a list of ingredients or upload an image, which the CNN processes to identify ingredients. This list is sent to the server, which generates a unique identifier (UUID) and launches a background thread to run LLaMA2 for token-by-token recipe generation. These tokens are streamed to a Firestore database under the associated UUID.

The client polls the database every two seconds to fetch new tokens, allowing the user to view the recipe incrementally in real time. This streaming approach enhances interactivity without waiting for the full 1–2 minute generation cycle.

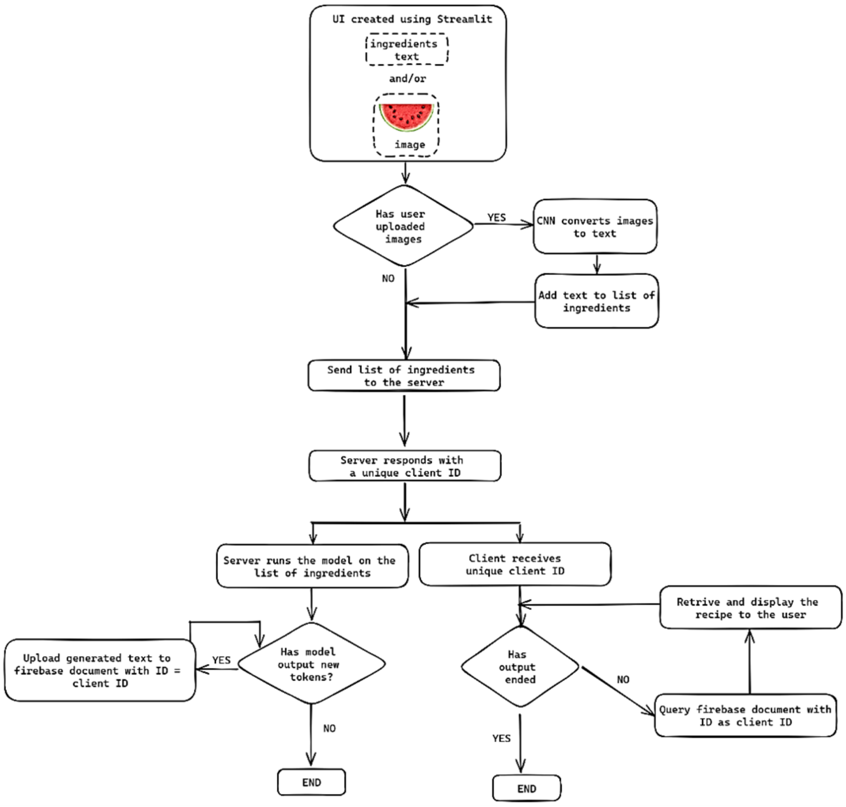


Figure 1 High-level block diagram of the proposed system architecture

3.2 Creating the CNN for Ingredient Identification

CNN development began with dataset loading and preprocessing using `tf.keras.utils.image_dataset_from_directory()`, resizing images to 64×64 in RGB format. This ensured consistency for training. The CNN architecture, defined in TensorFlow, comprised convolutional layers for feature extraction, pooling layers for downsampling, and fully connected layers for classification.

It was designed to balance performance and computational efficiency. The model was compiled with a suitable optimiser and loss function, using accuracy as the primary evaluation metric. Training was conducted using the `fit()` method with batches of 32 samples, across multiple epochs. Validation metrics were monitored to assess generalisation and detect overfitting. After achieving satisfactory performance, the model was saved in `.h5` format as `trained_model.h5`, making it ready for deployment without requiring retraining.

3.3 Fine-tuning Meta LLaMA2 for Recipe Generation

The Meta LLaMA2 model was fine-tuned using the RecipeNLG dataset containing approximately two million recipes, accessed and preprocessed via the Huggingface Datasets library. Ingredient names, often embedded with quantities, and newline-separated instructions were cleaned and reformatted using FoodBERT to suit prompt templates aligned with LLaMA2 documentation. The prompt-structured dataset was uploaded to the Huggingface Hub and fine-tuned on Google Colaboratory using an NVIDIA T4 GPU. Among several LLaMA2-7B checkpoints, the chat-optimised variant was selected for its superior output quality. Memory constraints were addressed by sharding across CPU, GPU, and disk, and fine-tuning was implemented using QLoRA (Quantised Low-Rank Adapters), enabling 4-bit weight quantisation for memory efficiency. The training loop, managed via the `SFTTrainer` class from Accelerate and BitsAndBytes, used a learning rate of $1e$–5, LoRA attention size of 64, LoRA alpha of 16, and a dropout rate of 0.1. Training was limited to one epoch and 1000 steps, after which adapter weights were saved and published to Huggingface Hub. The same configuration was reused to fine-tune GPT-2 and Mistral 7B Instruct models for comparative analysis.

3.4 Deployment

The trained models were integrated into a web-based system combining Streamlit for the client and Flask for the server. The CNN model (`trained_model.h5`) was deployed client-side using Streamlit to process user-inputted text or uploaded images for ingredient recognition. On the server side, a Flask application hosted on Google Colaboratory (exposed via Ngrok) received the processed ingredient list, generated a UUID, and initiated inference using the fine-tuned LLaMA2 model. Generated recipe tokens were incrementally written to a Firestore database under the corresponding UUID.

The client polled the database every two seconds, enabling real-time recipe display. This deployment ensured smooth integration between client-side recognition and server-side generation, demonstrating the practical use of large language models in resource-constrained environments while offering a responsive and user-friendly interface.

4 Results and Discussion

4.1 Ingredient Identification Results

The CNN model demonstrated consistent accuracy in identifying food ingredients from images. For instance, as shown in Figure 2, a sample beetroot image was correctly classified, confirming the model's generalisation on unseen data. The Streamlit interface enabled real-time user interaction and immediate prediction feedback.

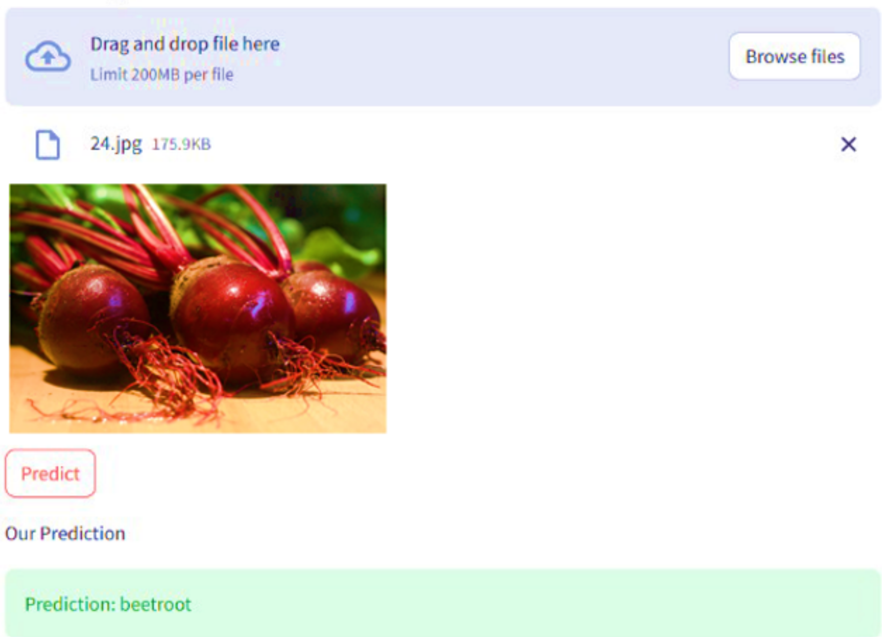
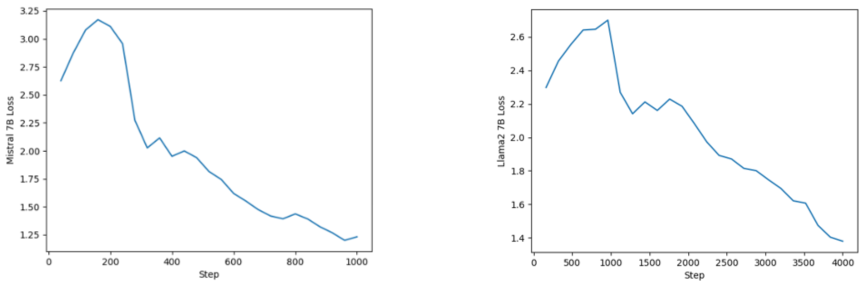


Figure 2 Prediction of ingredient from image using CNN model (Classified as beetroot)

4.2 Training Loss Analysis

Figure 3 shows the loss curves for LLaMA2 7B and Mistral 7B. LLaMA2's loss reduced steadily from 2.6 to below 1.4 over 4000 steps, indicating stable convergence. Mistral, though trained for fewer steps, showed a sharper drop from 3.2 to 1.25. Both models exhibited successful fine-tuning, with LLaMA2 achieving smoother convergence over a longer duration.



(a) LLaMA2 7B model (b) Mistral 7B model

Figure 3 Training loss vs. number of steps for LLaMA2 and Mistral 7B models

4.3 Evaluation Metrics

Model performance was assessed using BLEU, Brevity Penalty, and ROUGE-L scores, as summarised in Table 1. LLaMA2 7B achieved a BLEU score of 0.19 and ROUGE-L of 0.28, outperforming Mistral 7B. While GPT-2 showed a higher BLEU score, it incurred a brevity penalty due to its shorter outputs.

Table 1 Model performance based on BLEU, Brevity Penalty, and ROUGE-L

Model	**BLEU**	**Brevity Penalty**	**ROUGE-L**
LLaMA2 7B	0.19	1.0	0.28
Mistralv0.2 Instruct 7B	0.13	1.0	0.21
GPT-2 335M(Lee et al., 2020)	8.85	0.71	0.37

4.4 Recipe Generation Interface

The Streamlit interface enabled real-time recipe generation from both text and image inputs. As shown in Figure 4, a sample output for a watermelon and tomato salad demonstrates dynamic display of generated tokens retrieved via UUID from Firestore. This progressive rendering enhanced interactivity by eliminating long wait times.

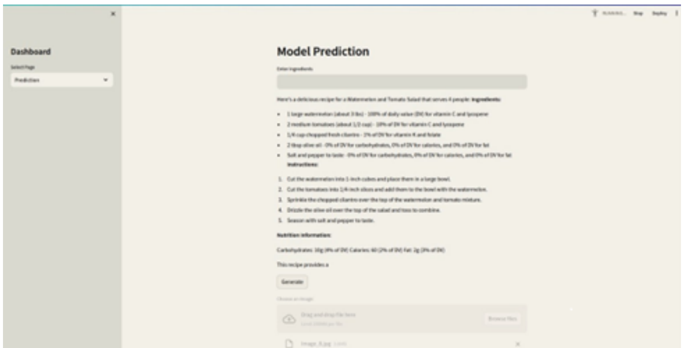


Figure 4 Recipe generation interface showing a watermelon, tomato, and coriander salad recipe

5 Conclusion

This study presents an integrated system for automated recipe generation by combining CNN-based ingredient recognition with natural language generation using a fine-tuned Meta LLaMA2 model. The system supports input from both text and food images, providing real-time, interactive recipe generation through a Streamlit-Flask deployment pipeline. Parameter-efficient fine-tuning via QLoRA enabled the model to perform effectively within hardware-constrained environments. Evaluation metrics such as BLEU and ROUGE-L validated the quality of the generated recipes, with the LLaMA2 model outperforming GPT-2 and Mistral variants. The interface offered smooth interaction and immediate feedback, highlighting the system's potential for practical use in culinary AI applications. Looking ahead, future enhancements include extending training over multiple epochs on high-memory GPUs and introducing validation sets to improve generalization. Incorporating culturally diverse datasets—particularly traditional Indian recipes annotated with spice profiles and cooking styles—can enhance localization.

Technically, alternative fine-tuning approaches like Representation Fine-Tuning (ReFT) may further boost efficiency. Additional features such as dietary filters, ingredient substitutions, and reinforcement learning-based user feedback could enhance personalization and health relevance. Overall, the proposed system sets the groundwork for intelligent, culturally adaptive, and user-aware digital kitchen assistants and recipe recommendation tools.

References

[1] J.M. Pilcher. *Food in World History*. Routledge, 2023.

[2] M. Sadhale. The concept of home cooks and its entrepreneurial business potential during and post COVID-19 pandemic. *International Journal of Future Generation Communication and Networking*, 14(1):1752–1772, 2021.

[3] P. Ma, Y. Li, M. Xu, and X. Liu. Large language models in food science: Innovations, applications, and future. *Trends in Food Science & Technology*, 2024.

[4] X. Tu, Y. Ma, Q. Huang, and X. Zhang. An overview of large AI models and their applications. *Visual Intelligence*, 2(1):1–22, 2024.

[5] H. Touvron, L. Martin, K. Stone, et al. LLaMA 2: Open foundation and fine-tuned chat models. Technical Report, Meta AI, 2023.

[6] M.A.K. Raiaan, M.S. Hossain, A. Shahjalal, and M.M. Hassan. A review on large language models: Architectures, applications, taxonomies, open issues and challenges. *IEEE Access*, 12:26839–26874, 2024.

[7] H. Naveed, T. Ahmad, A. Iqbal, and A. Majeed. A comprehensive overview of large language models. *arXiv preprint arXiv:2307.06435*, 2023.

[8] T. Wolf, L. Debut, V. Sanh, et al. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, 2020.

[9] M. Bień, P. Suwała, and K. Kajdanowicz. RecipeNLG: A cooking recipes dataset for semi-structured text generation. In *Proceedings of the 13th International Conference on Natural Language Generation*, pages 22–28, 2020.

[10] J. Marín, H. Wang, N. Ahuja, and A. Torralba. Recipe1M+: A dataset for learning cross-modal embeddings for cooking recipes and food images. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 43(1):187–203, 2021.

[11] M.S. Rodrigues, J.R. Oliveira, and F.J. Soares. RecipeIS—Recipe recommendation system based on recognition of food ingredients. *Applied Sciences*, 13(13):7880, 2023.

[12] M.K. Morol, M.M. Hossain, M.T. Hasan, and M.H. Kabir. Food recipe recommendation based on ingredients detection using deep learning. In *Proceedings of the 2nd International Conference on Computing Advancements*, pages 191–198, 2022.

[13] H. Muresan and M. Oltean. Fruit recognition from images using deep learning. *Acta Universitatis Sapientiae, Informatica*, 10(1):26–42, 2018.

Biography

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Effect of Salt Bath Nitriding Temperature on Electrochemical Corrosion Behavior of Al 7075

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Abstract

Aluminium (Al) alloys are widely used in aerospace and marine applications due to their high strength-to-weight ratio and thermal conductivity. However, Al 7075 is susceptible to pitting corrosion, which compromises its structural performance. While plasma nitriding improves surface characteristics, it is cost-intensive and time-consuming. This study proposes an economical salt bath nitriding method using a KNO_3 bath at 400°C, 450°C, and 475°C for 3 hours. Results indicate that nitriding temperature positively influences AlN layer thickness and micro-hardness. The 475°C-treated sample exhibited nearly double the hardness of the solution-annealed alloy. Electrochemical analysis revealed a substantial enhancement in corrosion resistance, with a tenfold reduction in corrosion current density compared to the untreated sample. These findings establish salt bath nitriding as a practical surface engineering method for improving the corrosion and mechanical properties of Al 7075.

Keywords: Aluminium alloy; Salt bath nitriding; Corrosion; Hardness; Surface engineering.

River Journal, 11–21.

1 Introduction

Corrosion is an irreversible degradation process that occurs when materials react with their environment. Though unavoidable, its effects can be mitigated through surface engineering techniques such as shot peening, powder coating, carburizing, and nitriding. Among these, nitriding offers significant advantages for aluminium (Al) alloys, improving the surface hardness and corrosion resistance without altering the core microstructure [1]. Al 7075, a high-strength structural alloy, is commonly used in aircraft and marine applications but suffers from poor pitting resistance. Various studies have investigated ion implantation and plasma nitriding to address this limitation. McCafferty et al. reported enhanced pitting resistance in nitrogen-implanted pure aluminium [2], while Massiani et al. demonstrated the formation of a 200nm AlN layer on Al-Cu alloys, improving corrosion resistance in Na_2SO_4 environments [3]. Plasma-based ion implantation also yielded promising results for Al 6061 and Al 2025 [4, 5], though these methods remain cost- and time-intensive, limiting their industrial scalability. As an alternative, gas and salt bath nitriding have gained interest due to their cost-effectiveness and process simplicity. Girish et al. employed ammonia gas nitriding on reinforced Al 6061 and observed improved corrosion performance [8]. Hamdy et al. demonstrated that salt bath nitriding using KNO_3 at 475°C enhanced corrosion resistance in Al 2024, particularly when followed by water quenching to ensure uniform AlN distribution [9]. In this context, the present work investigates salt bath nitriding of Al 7075 alloy at 400°C, 450°C, and 475°C, each for a duration of 3 hours in a fused KNO_3–KNO_2 bath. This study focuses on the correlation between nitriding temperature and AlN layer thickness, hardness enhancement, and corrosion resistance as assessed through scanning electron microscopy (SEM), X-ray diffraction (XRD), and potentiodynamic polarisation techniques.

2 Materials and Methods

2.1 Material Preparation

Commercial Al 7075 alloy with the chemical composition shown in Table 1 was used. Sheets of 7 mm thickness were sectioned into 1 cm $\times$ 1 cm coupons using wire electrical discharge machining (EDM). Samples were cleaned in deionised (DI) water via ultrasonic agitation for 10 minutes, then solution annealed at 480°C for 1 hour in a muffle furnace and water quenched.

Table 1 Chemical composition of Al 7075 alloy.

Element	Zn	Mg	Cu	Fe	Si	Mn	Cr	Al
Wt.%	5.6	2.5	1.6	0.5	0.4	0.3	0.23	Bal.

2.2 Sample Preparation

Solution-annealed (SA) samples were mechanically polished using SiC abrasive papers from 600 to 2500 grit, followed by fine polishing with 3 μm alumina slurry on velvet cloth to eliminate surface scratches. A final 10-minute ultrasonic cleaning in DI water was performed before nitriding.

2.3 Salt Bath Nitriding Process

Nitriding was conducted in a fused KNO_3 salt bath with a small amount of KNO_2 added to suppress volatilisation. The process was carried out in a graphite crucible within a muffle furnace, ensuring the molten salt fully covered the samples. SA-polished specimens were suspended in the bath using copper wire and nitrided at 400°C, 450°C, and 475°C for 3 hours. Post-nitriding, the samples were quenched in DI water and cleaned in an ultrasonic bath to remove residual salt.

2.4 Characterisation of Nitrided Layer

Cross-sectional SEM analysis was performed using a JEOL JSM-6380A microscope with Oxford EDS detector to measure nitride layer thickness and element distribution. Samples were prepared by mirror polishing transverse cross-sections. Phase identification was conducted via X-ray diffraction (XRD) using a PANalytical X'Pert Pro diffractometer with Cu Kα radiation (45 kV, 40 mA) over a 2θ range of 32–90°. Peak analysis was done using X'Pert HighScore software and matched with ICDD standards.

2.5 Micro-Hardness Testing

Micro-hardness measurements were performed using a Mitutoyo HM-112 Vickers microhardness tester. A 100 g load was applied for 10 seconds. Average hardness values were obtained from multiple indentations on each sample.

2.6 Electrochemical Corrosion Testing

Corrosion behaviour was evaluated via potentiodynamic polarisation (PDP) using a Bio-Logic potentiostat with frequency response analyser in a three-electrode setup. Tests were conducted in 0.1 M NaCl solution prepared using Thermo Fisher NaCl and DI water. Open circuit potential was recorded for 3600 s before polarisation scans, which were performed from –500 mV to +100 mV (vs. OCP) at a scan rate of 0.5 mV/s. Tafel extrapolation was used to determine corrosion potential (E_{corr}) and current density (i_{corr}). Post-testing, samples were ultrasonically cleaned and dried. SEM imaging was used to observe surface morphology after corrosion.

3 Results and Discussion

3.1 Characterisation of the Nitrided Layer

3.1.1 X-ray Diffraction (XRD)

The XRD patterns of the solution-annealed (SA) and nitrided Al 7075 samples are shown in Figure 1. The SA sample exhibited characteristic aluminium peaks at 2θ = 38.27°, 44.49°, 64.88°, and 78.00°, corresponding to the (111), (002), (022), and (311) planes. These sharp reflections, with no visible intermetallic peaks, confirm the dissolution of precipitates during the SA process. Nitrided samples revealed additional peaks corresponding to AlN, confirming nitride layer formation. The AlN peak intensity increased with nitriding temperature, indicating greater AlN phase fraction at elevated temperatures. A slight peak shift towards higher 2θ values was also observed, attributed to lattice distortion due to interstitial nitrogen. Literature confirms that nitrogen's limited solubility in Al promotes AlN phase formation over solid solution [9]. Furthermore, peaks corresponding to Mg_2Zn_{11} precipitates were noted in nitrided samples. Their increased density and size at higher temperatures suggest thermal growth of precipitates during prolonged exposure.

3.1.2 Energy Dispersive Spectroscopy (EDS)

EDS elemental mapping (Figure 2) was used to visualize nitrogen distribution on nitrided surfaces. Uniform nitrogen distribution was observed in all samples, with increasing nitrogen concentration at higher nitriding temperatures. The 475°C sample exhibited the densest nitrogen presence, indicating enhanced diffusion at elevated temperatures.

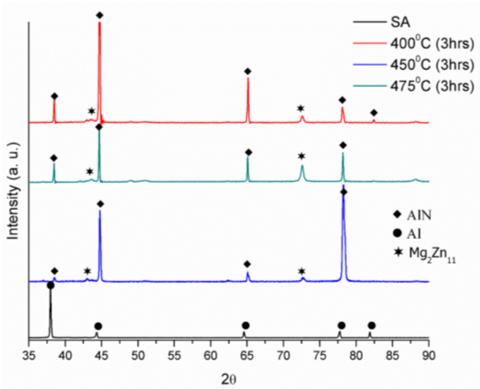

Figure 1 XRD patterns of SA and nitrided Al 7075 samples at various temperatures.

Some nitrogen-lean zones were observed near Mg_2Zn_{11} precipitates, possibly due to their interference with nitrogen uptake.

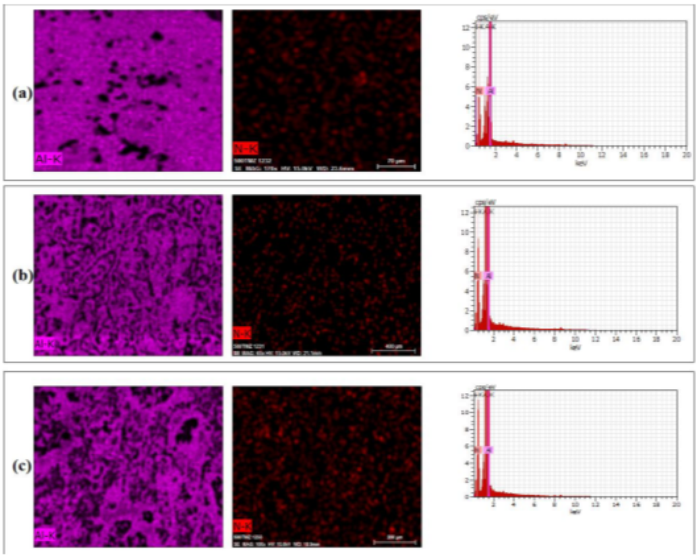

Figure 2 EDS nitrogen mapping of samples nitrided at (a) 400°C, (b) 450°C, and (c) 475°C.

3.1.3 Scanning Electron Microscopy (SEM)

SEM micrographs of transverse cross-sections (Figure 3) revealed compact AlN layers formed at all three temperatures. Layer thickness increased from 2.54 μm (400°C) to 4.95 μm (475°C), as shown in Figure 4. The nitride layer appeared dense, with no visible porosity or delamination at the interface. Nitriding at higher temperatures accelerates AlN formation due to increased diffusion rates. Given nitrogen's negligible solubility in aluminium, Al diffuses outward to react with nitrogen, forming a surface-bound AlN layer [5]. The layer's confinement to the sub-surface confirms a typical compound-type case structure.

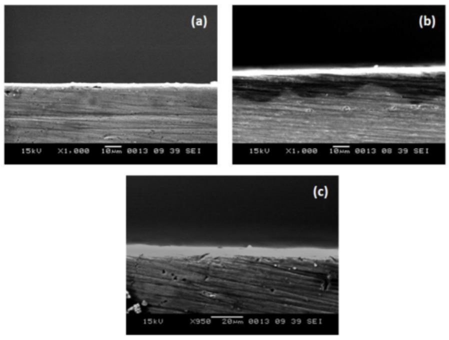

Figure 3 SEM images of Al 7075 cross-sections nitrided at (a) 400°C, (b) 450°C, and (c) 475°C.

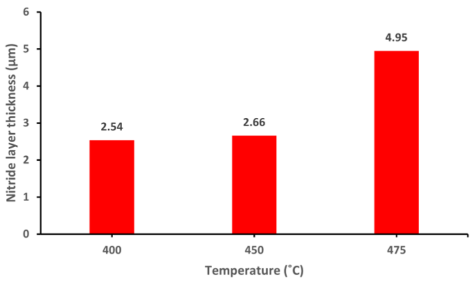

Figure 4 Comparison of AlN layer thickness at different nitriding temperatures.

3.2 Micro-Hardness Analysis

Figure 5 shows the variation in Vickers micro-hardness of SA and nitrided Al 7075 samples. The SA alloy exhibited a baseline hardness of 106 HV. Nitriding significantly enhanced hardness, with values increasing to 143.1 HV at 400°C, 178.8 HV at 450°C, and 209.1 HV at 475°C. This increase is attributed to the formation of a hard AlN surface layer, which impedes dislocation motion. Additionally, Mg_2Zn_{11} precipitates formed during nitriding may contribute to hardening, although their excessive growth can reduce strengthening efficiency. Literature suggests that post-nitriding re-ageing can restore or further enhance hardness if precipitate coarsening occurs [11].

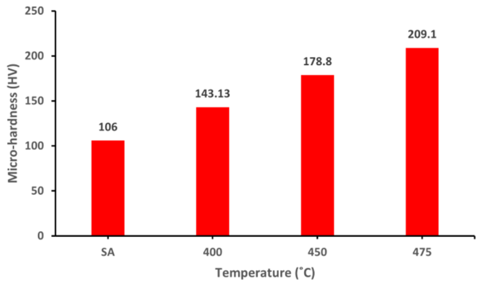

Figure 5 Vickers micro-hardness of SA and nitrided Al 7075 samples.

3.3 Electrochemical Testing

The corrosion performance of SA and nitrided samples was evaluated using potentiodynamic polarisation (PDP) in 0.1 M NaCl. Figure 6 presents the Tafel plots, and corresponding E_{corr} and i_{corr} values are summarised in Table 2. The SA sample showed the highest corrosion current density (2.57×10^{-5} μA/cm^2), while the 475°C nitrided sample recorded the lowest (9.52×10^{-7} μA/cm^2), indicating a 27-fold reduction. The corrosion potential (E_{corr}) shifted in the noble direction with increasing nitriding temperature, affirming improved thermodynamic stability. The cathodic region slope indicates that the corrosion process is cathodically controlled. The AlN layer acts as a physical and chemical barrier, reducing ion/electron transport and inhibiting electrochemical reactions. The enhanced charge transfer resistance at higher temperatures aligns with the increase in nitride layer thickness. Post-corrosion SEM analysis (Figure 7) revealed extensive pitting in the SA sample, while nitrided surfaces showed fewer and shallower pits.

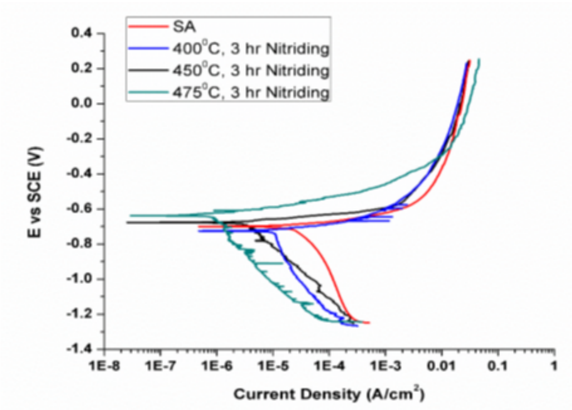

Figure 6 Potentiodynamic polarisation curves for SA and nitrided Al 7075 samples.

Table 2 Corrosion potential and current density values of tested samples.

Sample	E_{corr} (mV vs. OCP)	i_{corr} (μA/cm^2)
SA	–	2.57×10^{-5}
400°C	Shifted Noble	1.65×10^{-5}
450°C	Shifted Noble	5.50×10^{-6}
475°C	Most Noble	9.52×10^{-7}

The 475°C sample showed minimal damage, demonstrating the role of a well-formed AlN layer in pitting resistance. Precipitates like Mg_2Zn_{11} can act as local cathodes, promoting galvanic corrosion, but a uniformly distributed AlN layer reduces such effects [12].

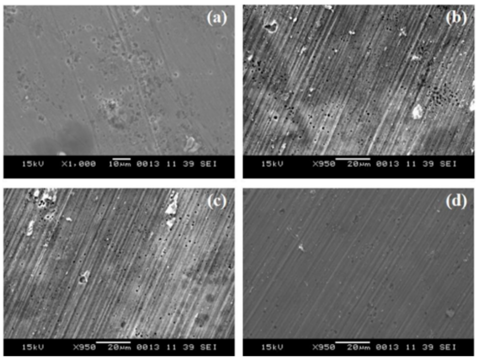

Figure 7 SEM images after corrosion: (a) SA, (b) 400°C, (c) 450°C, (d) 475°C.

4 Conclusion

This study evaluated the influence of salt bath nitriding temperature on the surface hardness and electrochemical corrosion resistance of Al 7075 alloy. Based on the results, the following conclusions are drawn:

1. Salt bath nitriding using a KNO_3–KNO_2 fused salt mixture effectively forms an AlN surface layer on Al 7075. The thickness of the nitride layer increased with higher nitriding temperatures.
2. A direct correlation was observed between nitride layer thickness and micro-hardness. The sample nitrided at 475°C exhibited the highest hardness, nearly double that of the solution-annealed alloy.
3. Potentiodynamic polarisation testing revealed enhanced corrosion resistance with increasing nitriding temperature. The corrosion current density reduced by over an order of magnitude for the 475°C-treated sample.
4. Post-corrosion surface analysis confirmed reduced pitting in nitrided samples. The uniform and compact AlN layer acted as a barrier against ion diffusion and galvanic effects, especially at elevated nitriding temperatures.
5. Salt bath nitriding emerges as a cost-effective, time-efficient, and scalable technique for improving the mechanical and corrosion properties of Al 7075 alloys, offering a promising alternative to plasma and ion implantation methods for industrial surface engineering applications.

References

[1] C.X. Li and T. Bell. A comparative study of low temperature plasma nitriding, carburising and nitrocarburising of AISI 410 martensitic stainless steel. *Materials Science and Technology*, 23(3):355–361, 2007.

[2] E. McCafferty, P.M. Natishan, and G.K. Hubler. Pitting behavior of aluminum ion implanted with nitrogen. *Corrosion*, 53(7), 1997.

[3] Y. Massiani, J. Creus, P. Bonino, and M. Touzet. Electrochemical study of multiple-energy nitrogen-ion-implanted aluminium alloys. *Materials Science and Engineering A*, 116:53–57, 1989.

[4] L. Zhang, T. Takahashi, Y. Ueda, and S. Miyazaki. Anti-corrosive surface modification of 6061 aluminum using plasma source ion implantation. *Materials Letters*, 22(1–2):29–33, 1995.

[5] M. Moradshahi, S.M. Rozati, and S.M. Aghaei. Plasma nitriding of Al alloys by DC glow discharge. *Surface and Coatings Technology*, 201(3–4):567–574, 2006.

[6] D. Pye. *Practical Nitriding and Ferritic Nitrocarburizing*. ASM International, 2003.

[7] *Heat Treatment: Conventional and Novel Applications*. IntechOpen, 2012.

[8] B.M. Girish, M. Somashekar, S. Basavarajappa, and V.S. Aithal. Effect of nitriding on corrosion behaviour of graphite reinforced aluminium alloy composites. *Corrosion Engineering, Science and Technology*, 48(1):51–54, 2013.

[9] A.S. Hamdy, M. El-Kashif, and A.A. El-Bellihi. Electrochemical studies on the film formed by direct nitridation of AA2024 in a KNO_3 salt bath. *Materials Chemistry and Physics*, 127(1–2):253–258, 2011.

[10] N. Khan, A.A. Khan, M. Qasim, and M. Abdullah. Nitriding of aluminium alloy in nitrogen and nitrogen-helium mixture using pulsed DC glow discharge. *Plasma Science and Technology*, 12(4):452–460, 2010.

[11] R.J. Flynn and J.S. Robinson. Application of quench factor analysis to the heat treatment of 7010 aluminium alloy. *Journal of Materials Processing Technology*, 153–154:1021–1026, 2004.

[12] C.D. Lee, S.H. Han, and S.K. Hong. Effect of galvanic corrosion between precipitate and matrix on corrosion behaviour of as-cast magnesium-aluminum alloys. *Metals and Materials*, 6:351–358, 2000.

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Advancements in Parkinson's Disease Detection using Machine Learning

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Abstract

This study presents a machine learning-based approach to enhance the detection of Parkinson's disease (PD) using classification models such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Naïve Bayes, and Logistic Regression. Leveraging a publicly available dataset, the proposed framework addresses challenges in feature selection, data diversity, and model interpretability. Preprocessing techniques were employed to ensure data quality, including standard scaling and class distribution analysis. Model performance was evaluated using accuracy, precision, recall, and F1-score metrics. Among the tested models, KNN achieved the highest accuracy of 90% and F1-score of 0.93, indicating strong diagnostic capability. The system provides healthcare practitioners with interpretable results through visual outputs, enabling informed clinical decision-making. This work demonstrates the potential of accessible, data-driven methods for early PD detection and lays the groundwork for future improvements through longitudinal analysis and multi-modal data integration.

Keywords: Parkinson's disease, machine learning, SVM, KNN classifier, Naïve Bayes, Logistic Regression, feature selection, model evaluation.

River Journal, 22–31.

1 Introduction

Parkinson's disease (PD) is a progressive neurodegenerative disorder that primarily affects motor functions and significantly impacts the quality of life. Early and accurate diagnosis remains a clinical challenge due to overlapping symptoms with other conditions and the absence of definitive biomarkers. Recent advances in machine learning (ML) have shown promise in aiding medical diagnostics by uncovering patterns in clinical and physiological data that may not be evident through traditional methods. This study investigates the application of ML algorithms—Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Naïve Bayes, and Logistic Regression—for the early detection of Parkinson's disease. These models are trained on a publicly available dataset consisting of biomedical voice measurements known to be affected by PD. The aim is to evaluate and compare the performance of each model in distinguishing between healthy individuals and PD patients based on extracted features. By integrating statistical analysis and performance metrics such as precision, recall, and F1-score, the research highlights the diagnostic capabilities of each classifier. The work also emphasizes the need for interpretable models in clinical settings and the potential for machine learning to augment healthcare diagnostics. This research contributes to the development of accessible, data-driven tools for improving early Parkinson's detection.

2 Literature Survey

Parkinson's disease (PD) is difficult to diagnose in its early stages, leading to growing interest in machine learning (ML) approaches for its detection and progression analysis. Several studies have demonstrated the effectiveness of ML in identifying PD from biomedical data, particularly voice features. Nilashi et al. [1] evaluated ensemble methods for predicting Unified Parkinson's Disease Rating Scale (UPDRS) scores, noting the challenge of effective feature selection. Radha et al. [2] used MFCC, spectral centroid, and RMS features from speech samples, applying CNN, ANN, and HMM models. ANN achieved the highest accuracy (96.2%). Alalayah et al. [3] improved early PD detection through feature selection (RFE), data balancing (SMOTE), and dimensionality reduction (t-SNE, PCA). Their multilayer perceptron with PCA reached 98% accuracy. Similarly, Shraddha et al. [4] employed SVM and MFCC features on 195 voice samples, achieving 89% accuracy.

García-Ordás et al. [5] combined classification and regression deep learning models to assess PD severity using UPDRS scores, achieving 99.15% classification accuracy. Templeton et al. [6] used tablet-based digital biomarkers and decision trees, achieving 92.6% accuracy in distinguishing PD patients. XGBoost classifiers with MRMR and RFE-based feature selection also performed well in studies by Priyadharshini et al. [7] and Patil et al. [8], both reporting over 92% accuracy. Wroge et al. [9] used mPower voice recordings and decision tree ensembles, obtaining 86% accuracy and suggesting the integration of multiple data modalities. Other studies such as Govindua et al. [10] reported promising results using SVM, KNN, and Random Forests with PCA. Mei et al. [11] conducted a comprehensive review of 209 ML-based PD studies, highlighting limitations in reproducibility and clinical translation. Saeed et al. [12] combined wrapper-based feature selection with KNN to achieve 88.33% accuracy. Varghese et al. [13] showed that support vector regression outperformed other models in predicting PD severity from speech data. Overall, the literature highlights the potential of ML in PD detection but also reveals persistent gaps, such as limited data diversity, inconsistent validation practices, and challenges in model explainability. This study aims to address these through dataset augmentation, optimized feature engineering, interpretable model development, and robust evaluation.

3 Methodology

The dataset used for this study was obtained from Kaggle in `.csv` format. Preliminary exploration involved assessing descriptive statistics and identifying missing values. The `name` column, being non-informative, was dropped. The target variable `status` was encoded as a binary value (0 or 1), and feature scaling was applied using `StandardScaler` to normalize the values—essential for models such as SVM, KNN, Logistic Regression, and Naïve Bayes. For data analysis, a count plot was used to assess class balance. A correlation heatmap was generated to explore feature interdependence (Figure 1), while box plots (Figure 2) highlighted variations in feature distributions between Parkinson-positive and negative cases. These visual tools helped identify patterns and validate the dataset's structure before modeling. Feature selection was not explicitly performed; all relevant features, aside from the dropped `name` column, were retained based on domain knowledge and exploratory data analysis. Four classifiers were trained and evaluated: Support Vector Machine (SVM), k-Nearest Neighbours (KNN), Naïve Bayes, and Logistic Regression.

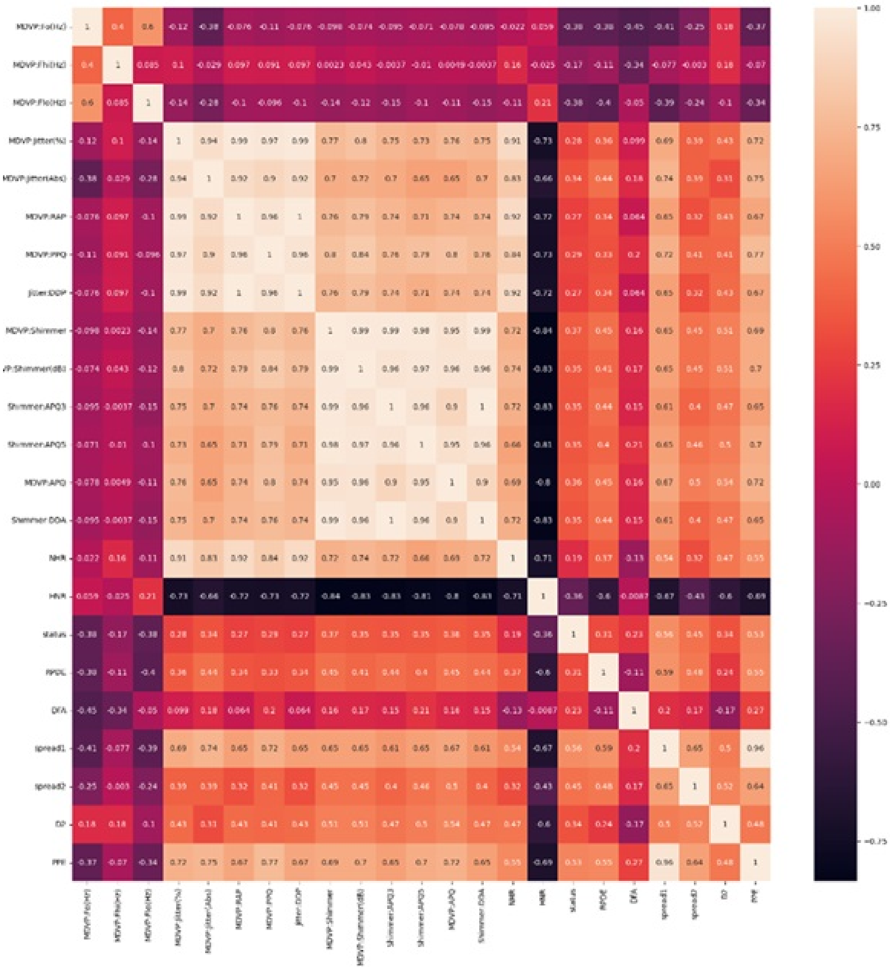


Figure 1 Correlation heatmap of features.

For each model, the dataset was split using `train_test_split`, and models were trained on the standardized training set. The SVM classifier used a linear kernel, while KNN was configured with $k = 5$ neighbors. Naïve Bayes followed the Gaussian distribution assumption, and Logistic Regression was trained with default hyperparameters. Model predictions were evaluated using accuracy, precision, recall, and F1-score on the testing set. Confusion matrices were also generated to visualize classification performance. The evaluation metrics were computed as follows:

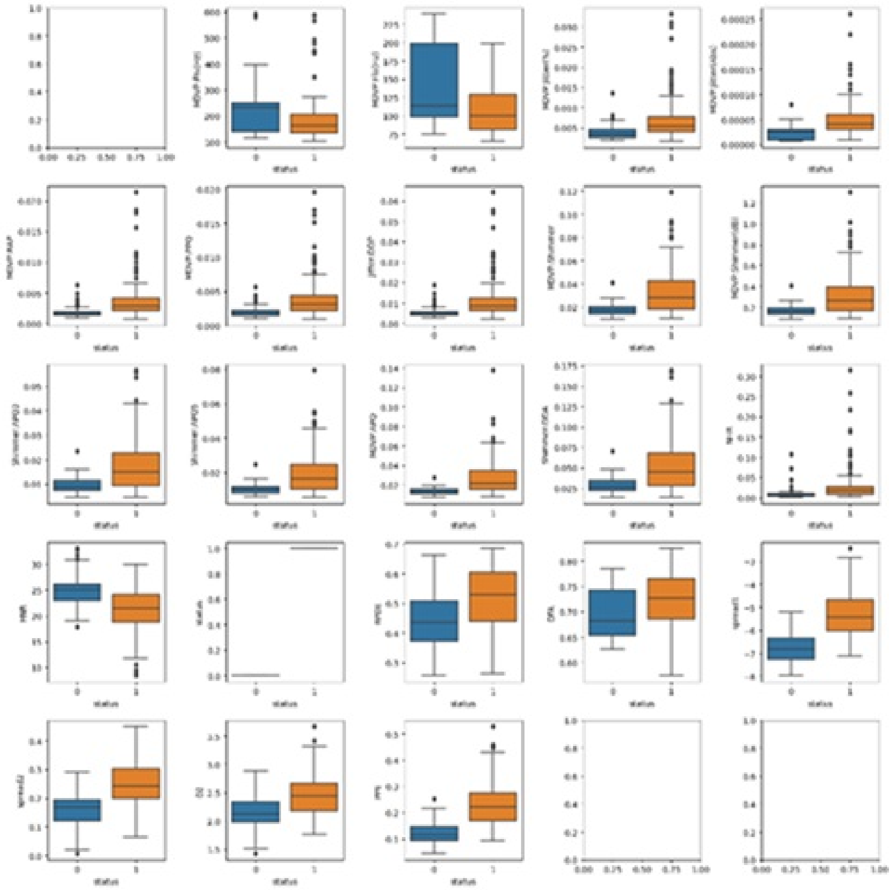


Figure 2 Box plots of selected features by class.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1-score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

where TP is true positives, TN true negatives, FP false positives, and FN false negatives. These metrics offered a comprehensive understanding of each model's ability to generalize and detect Parkinson's disease accurately.

4 Results and Discussion

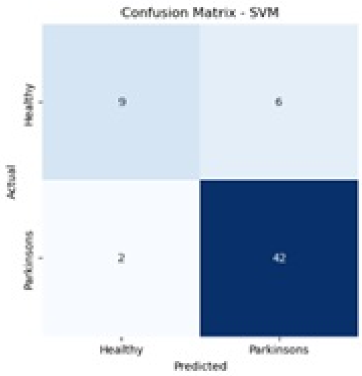
The performance of four machine learning models—SVM, KNN, Logistic Regression, and Naïve Bayes—was evaluated using standard classification metrics. The SVM and Logistic Regression models demonstrated similar performance, with high precision and recall, while the KNN model achieved the highest accuracy overall. Naïve Bayes performed comparatively lower, particularly in recall, indicating challenges in identifying positive cases. The evaluation was carried out on both training and testing datasets, and the results were visualized using confusion matrices (Figures 3(a) to 3(d)) and comparative performance plots (Figure 4).

The classification performance of all four models was visualized using confusion matrices, as shown in Figure 3. These matrices help highlight the distribution of true positives, true negatives, false positives, and false negatives, providing insights into each model's strengths and weaknesses. KNN and SVM models exhibit high true positive rates, while Naïve Bayes shows a higher false negative rate, indicating its limitations in correctly identifying PD-positive cases. The comparative metrics for all models—precision, recall, accuracy, and F1-score—are summarized in Table 1 and visualized in Figure 4.

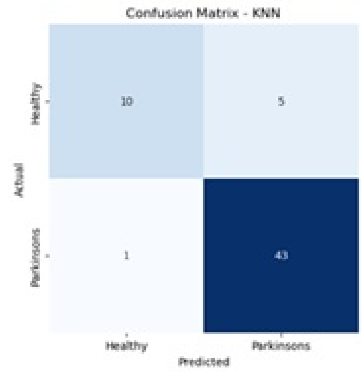
Table 1 Evaluation metrics of all the models

Model	**Precision**	**Recall**	**Accuracy**	**F1 Score**
SVM	0.8750	0.9545	0.8644	0.9130
KNN	0.8958	0.9773	0.9000	0.9348
NB	0.9167	0.7500	0.7627	0.8250
LR	0.8750	0.9545	0.8644	0.9130

The KNN model achieved the best overall performance with 90% accuracy and the highest F1-score (0.9348), indicating a balanced capability to minimize both false positives and false negatives. SVM and Logistic Regression followed closely, showing identical performance with strong recall (0.9545) and precision (0.8750). In contrast, Naïve Bayes, despite having the highest precision (0.9167), had a lower recall (0.7500), suggesting a higher rate of false negatives.

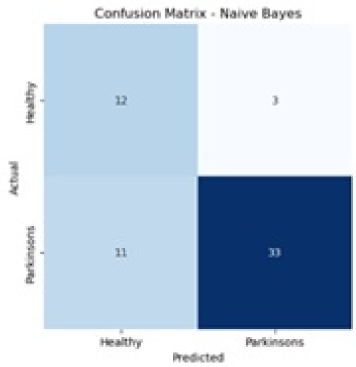


(a) SVM Model



(b) KNN Model

(c) Logistic Regression Model



(d) Naïve Bayes Model

Figure 3 Confusion matrices of all four classification models: (a) SVM, (b) KNN, (c) Logistic Regression, and (d) Naïve Bayes. Each matrix visualizes model performance across predicted and actual classes.

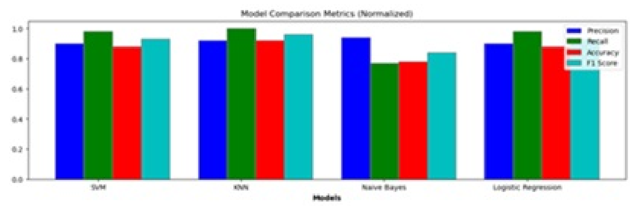


Figure 4 Comparison of evaluation metrics across all four models.

This indicates that while Naïve Bayes is more cautious in predicting positives, it may miss a larger proportion of true PD cases. These findings reaffirm the efficacy of non-linear distance-based models like KNN in handling subtle feature distributions in biomedical data, provided scaling and preprocessing are handled correctly.

5 Conclusion

This study explored the application of machine learning techniques for the early detection of Parkinson's disease (PD), focusing on four classifiers: Support Vector Machine (SVM), k-Nearest Neighbours (KNN), Logistic Regression (LR), and Naïve Bayes (NB). Among these, the KNN model outperformed others with the highest accuracy (90%) and F1-score (0.9348), indicating strong predictive capability and balance between precision and recall. Both SVM and Logistic Regression achieved comparable results, demonstrating high sensitivity and consistent precision. In contrast, Naïve Bayes, although yielding the highest precision (0.9167), suffered from lower recall (0.7500), suggesting limitations in correctly identifying PD-positive cases. These findings validate the use of supervised learning for reliable PD screening and support the development of data-driven tools in clinical diagnostics. To enhance future implementations, the study recommends the integration of longitudinal datasets, multi-modal feature fusion (e.g., voice, motor, handwriting, EEG), and transfer learning techniques. Additionally, efforts should be directed toward real-time deployment and clinical collaboration to improve usability and validation in healthcare settings. By addressing these directions, machine learning-driven PD detection systems can be made more accurate, interpretable, and impactful for early intervention and patient care.

References

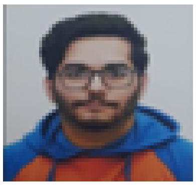
[1] M. Nilashi, R.A. Abumalloh, B. Minaei-Bidgoli, S. Samad, M.Y. Ismail, A. Alhargan, and W.A. Zogaan. Predicting Parkinson's disease progression: Evaluation of ensemble methods in machine learning. *Journal of Healthcare Engineering*, 2022:1–17, 2021.

[2] N. Radha, S.M. R.M., and S. Holy. Parkinson's disease detection using machine learning techniques. *Revista Argentina de Clínica Psicológica*, 30(2):543–552, 2021.

[3] K.M. Alalayah, E.M. Senan, H.F. Atlam, I.A. Ahmed, and H.S.A. Shatnawi. Automatic and early detection of Parkinson's disease by analyzing acoustic signals using classification algorithms based on recursive feature elimination method. *Diagnostics*, 13(11):1924, 2023.

[4] S.V. Bante, S.M. Barhate, and S.J. Sharma. Parkinson's disease detection using machine learning. *Journal of Emerging Technologies and Innovative Research*, 9(6):21–23, 2022.
[5] M.T. García-Ordás, J.A. Benítez-Andrades, J. Aveleira-Mata, J.M. Alija-Pérez, and C. Benavides. Determining the severity of Parkinson's disease in patients using a multi-task neural network. *Multimedia Tools and Applications*, 83:6077–6092, 2024.
[6] J.M. Templeton, C. Poellabauer, and S. Schneider. Classification of Parkinson's disease and its stages using machine learning. *Scientific Reports*, 12:14036, 2022.
[7] G. Priyadharshini, T. Gowtham, M.H. Bhoopathi, M. Reshma, V. Tamilarasi, and P. Nandhini. Detection of Parkinson disease using machine learning. *Engineering and Technology Journal for Research and Innovation*, 4(1):32–38, 2022.
[8] S. Patil, S. Jaybhaye, S. Bokariya, P. Jain, S. Phapale, and T. Hande. Parkinson's disease prediction system in machine learning. In *Proceedings of the First International Conference on Data Science and Advanced Computing (ICDSAC 2023)*, *ITM Web of Conferences*, 56:05002, 2023.
[9] T.J. Wroge, Y. Özkanca, C. Demiroglu, D. Si, D.C. Atkins, and R.H. Ghomi. Parkinson's disease diagnosis using machine learning and voice. In *Proceedings of the IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*, pages 1–7, 2018.
[10] A. Govindua and S. Palwe. Early detection of Parkinson's disease using machine learning. *Procedia Computer Science*, 218:249–261, 2023.
[11] J. Mei, C. Desrosiers, and J. Frasnelli. Machine learning for the diagnosis of Parkinson's disease: A review of literature. *Frontiers in Aging Neuroscience*, 13:633752, 2021.
[12] F. Saeed, M. Al-Sarem, M. Al-Mohaimeed, A. Emara, W. Boulila, M. Alasli, and F. Ghabban. Enhancing Parkinson's disease prediction using machine learning and feature selection methods. *Computers, Materials & Continua*, 71(3):5639–5658, 2022.
[13] B.K. Varghese, G.B.A.D. Amali, and U.D.K.S. Devi. Prediction of Parkinson's disease using machine learning techniques on speech dataset. *Research Journal of Pharmacy and Technology*, 12(2):644–648, 2019.

Biography



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Convolutional Neural Network-Based Stage Classification of Alzheimer's Disease Using MRI Scans

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Abstract

A convolutional neural network (CNN) framework is proposed for classifying Alzheimer's disease (AD) stages using high-resolution magnetic resonance imaging (MRI) data. The model is trained on a balanced dataset of approximately 12,000 scans, categorized into Mild Demented (MD), Moderate Demented (MoD), Very Mild Demented (VMD), Non-Demented (ND), and Healthy (H) classes. A comparative analysis of optimizers—including SGD, RMSprop, Adam, and Nadam—was conducted using a fixed learning rate of 0.001, where Adam achieved the highest classification accuracy of 99%. The model effectively differentiates between AD stages, enabling early diagnosis and informing clinical decision-making. Results underscore the critical role of optimizer selection and data diversity in developing robust CNN-based diagnostic tools.

Keywords: Alzheimer's disease, convolutional neural networks, MRI-based classification, Adam optimizer, diagnostic accuracy, neurodegenerative disorders.

River Journal, 32–42.

1 Introduction

Alzheimer's disease (AD) is a progressive neurodegenerative condition marked by cognitive decline, memory loss, and behavioural deterioration, primarily affecting the elderly. Its global prevalence is projected to exceed 130 million by 2050, underscoring the critical need for early and accurate diagnostic strategies [1]. The economic burden of delayed AD diagnosis further reinforces the need for timely intervention [10]. From a sociocultural perspective, AD also poses challenges related to identity and caregiving, as noted in contemporary narrative research [11]. Traditional diagnosis, relying on clinical assessment, often fails to detect early-stage AD, delaying timely intervention. Magnetic Resonance Imaging (MRI) offers a non-invasive method for visualising neurodegenerative changes, particularly in regions such as the hippocampus and cortex. Recent studies have shown promise in applying deep learning models, especially Convolutional Neural Networks (CNNs), to MRI data for AD diagnosis [13, 14]. Building on this foundation, this study proposes a CNN-based framework for stage-wise classification of AD using a large, balanced MRI dataset. The model is evaluated using various optimizers, and its performance demonstrates high diagnostic accuracy across five AD progression classes. Assistive software tools designed to stimulate cognitive memory in early-stage AD patients also complement such diagnostic frameworks [2].This approach highlights the role of AI in supporting clinical decision-making and improving early detection of neurodegenerative disorders.

2 Related Work

Recent advances in medical imaging and artificial intelligence have facilitated the development of automated tools for Alzheimer's disease (AD) diagnosis. Basaia et al. [13] employed a CNN model to classify AD from structural MRI data, achieving high accuracy. Similarly, Zhang et al. [14] applied Support Vector Machines (SVMs) on longitudinal MRI scans to differentiate AD from healthy subjects. Rahat et al. [15] explored deep learning models including DeepLabv3 and U-Net for FLAIR-based brain anomaly segmentation, highlighting the importance of architectural choice and data balancing in neuroimaging tasks. Melchiorri et al. [4] underscored the role of neuroinflammation and suggested that integrating imaging with molecular pathways could enhance diagnostic precision.

Additionally, Wang et al. [5] identified urine formaldehyde as a potential early-stage biomarker, reinforcing the value of non-invasive diagnostic approaches. These studies collectively demonstrate the efficacy of AI-driven models and biomarker-informed imaging in improving AD classification. Additionally, emotional and empathy-based assessments have been explored to distinguish AD from other dementia types [3]. Building on these efforts, this study presents a CNN framework trained on a large, multi-stage MRI dataset for accurate and scalable classification of AD progression.

3 Methodology

3.1 Dataset

This study employs a curated dataset of approximately 12,000 high-resolution MRI scans for Alzheimer's disease (AD) classification. The images are categorized into five classes: Mild Demented (MD), Moderate Demented (MoD), Very Mild Demented (VMD), Non-Demented (ND), and Healthy (H), representing various stages of AD progression. Class balance was maintained to prevent model bias and enhance generalization. The high-resolution nature of the scans enables detailed feature extraction, particularly for early-stage detection. The diversity and volume of this dataset provide a strong foundation for training a deep learning model capable of robust stage classification. Representative samples from each class are shown in Fig. 1.

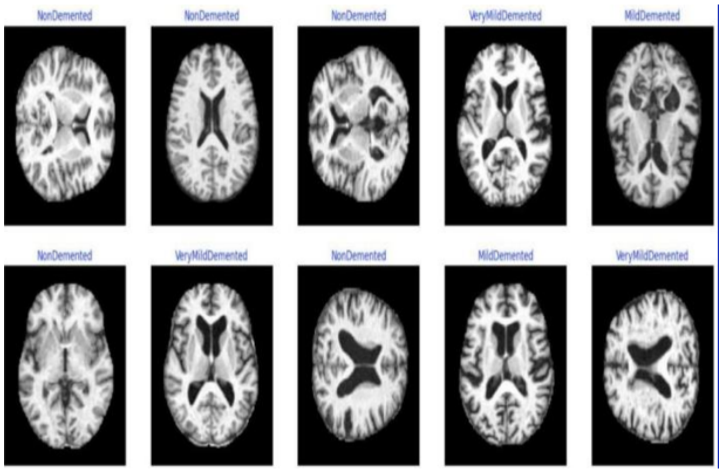

Figure 1 Sample images from the curated MRI dataset used for AD stage classification.

3.2 Image Preprocessing

To enhance model generalization and accuracy, a comprehensive preprocessing pipeline was implemented, incorporating both data augmentation and color-space transformations. Augmentation techniques such as random rotations ($\pm 10°$), translations (10%), scaling (0.9–1.1), horizontal flipping, elastic deformation, and brightness/contrast adjustments were applied to simulate anatomical and acquisition variability. Gaussian noise was also introduced to improve robustness against imaging artifacts. This augmentation strategy, visualized in Fig. 2, enriched the dataset without increasing storage.

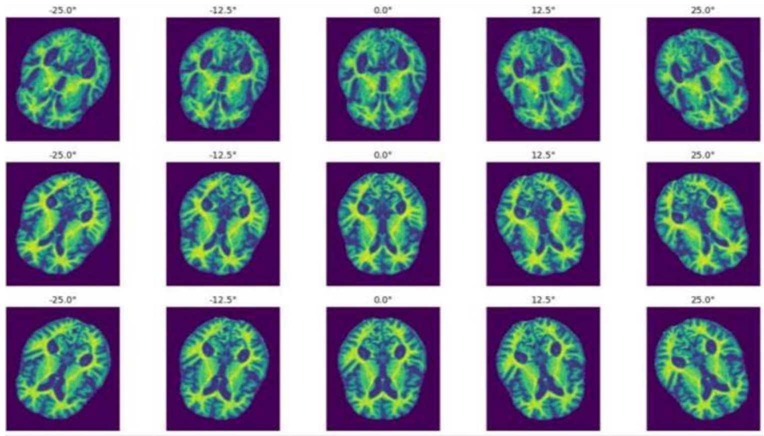

Figure 2 Data augmentation via rotational, translational, and elastic transformations applied to MRI scans.

In parallel, MRI scans were converted to grayscale to emphasize structural features, and further transformed into HSV, LAB, and YCbCr color spaces to enhance contrast and luminance-based feature extraction. These transformations facilitate the detection of subtle pathological patterns relevant to Alzheimer's classification. As illustrated in Fig. 3, multi-space encoding contributed to improved learning of cortical and subcortical abnormalities. This dual preprocessing approach ensured high model sensitivity to AD-specific anatomical variations, particularly in early-stage cases where structural changes are often subtle. Recent advancements in pose-aware 3D deep learning frameworks [12] may further enhance spatial encoding in future AD imaging models.

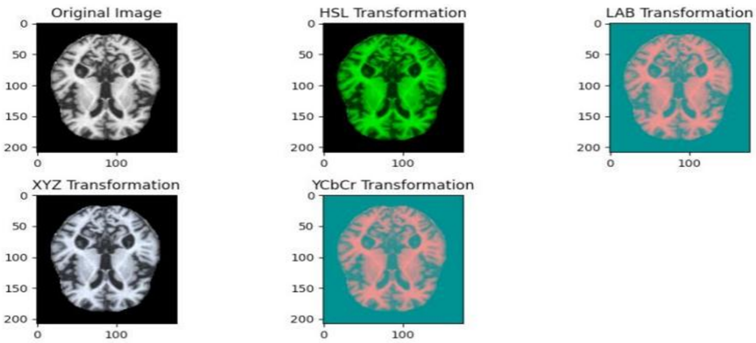

Figure 3 Comparative analysis of color-space transformations used for feature enhancement in MRI-based AD classification.

3.3 Model Architecture

A custom convolutional neural network (CNN) was developed to classify MRI scans into five Alzheimer's disease (AD) stages: Mild Demented, Moderate Demented, Very Mild Demented, Non-Demented, and Healthy. Input images were resized to 150×150 pixels with three channels and normalized via a rescaling layer. The architecture consists of two convolutional blocks, each comprising a convolutional layer with 3×3 filters followed by max pooling. The first block uses 32 filters, and the second uses 64, progressively capturing low-level to abstract spatial features. The extracted features are flattened and passed to a fully connected dense layer with 300 neurons, followed by a dropout layer to mitigate overfitting. The final output layer contains five neurons with softmax activation to predict the respective class probabilities. In total, the model comprises approximately 24.9 million trainable parameters. This architecture is optimized for extracting structural and textural features from MRI data and demonstrates strong potential for stage-wise classification in AD diagnosis.

4 Performance Analysis by Class

The proposed CNN model demonstrated consistently high classification performance across all five categories: Mild Demented, Moderate Demented, Very Mild Demented, Non-Demented, and Healthy. Precision, recall, and F1-scores ranged between 0.98 and 1.00 for all classes, as detailed in Table 1. The best performance was observed in the Moderate Demented and Non-Demented categories, both achieving near-perfect scores.

Very Mild Demented, often challenging due to subtle pathology, was classified with a precision of 0.99 and recall of 0.98, indicating the model's sensitivity to early-stage AD indicators. Healthy controls also yielded high classification accuracy with balanced precision and recall of 0.99. These results confirm the effectiveness of the proposed architecture in distinguishing AD stages and unaffected individuals. The confusion matrix illustrating the class-wise distribution of predictions is shown in Fig. 4, while Fig. 5 compares training and validation accuracy and loss trends across epochs.

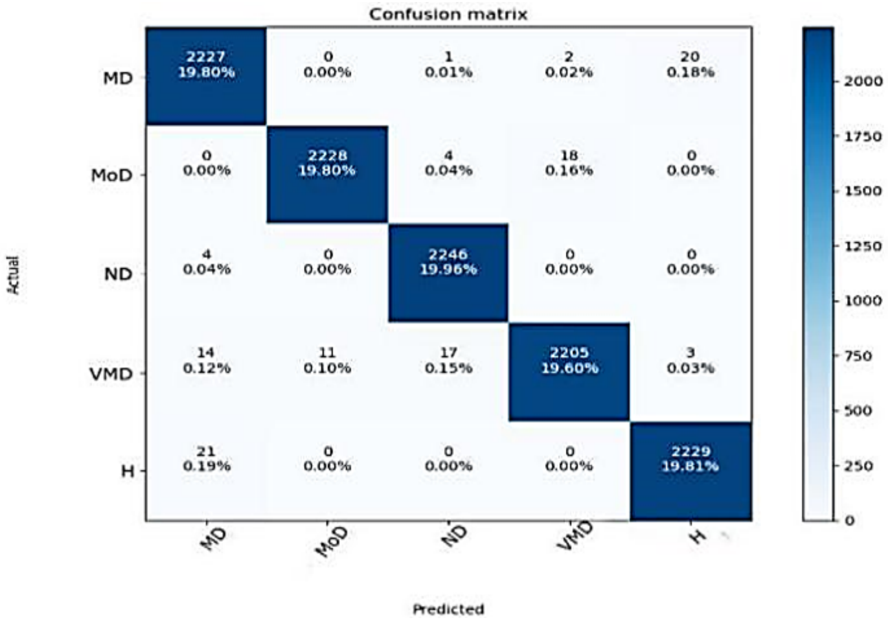

Figure 4 Confusion matrix representing classification performance across all AD stages and the healthy class.

5 Results and Analysis

The CNN model achieved high performance across all Alzheimer's disease (AD) stages, with precision, recall, and F1-scores ranging from 0.98 to 1.00.

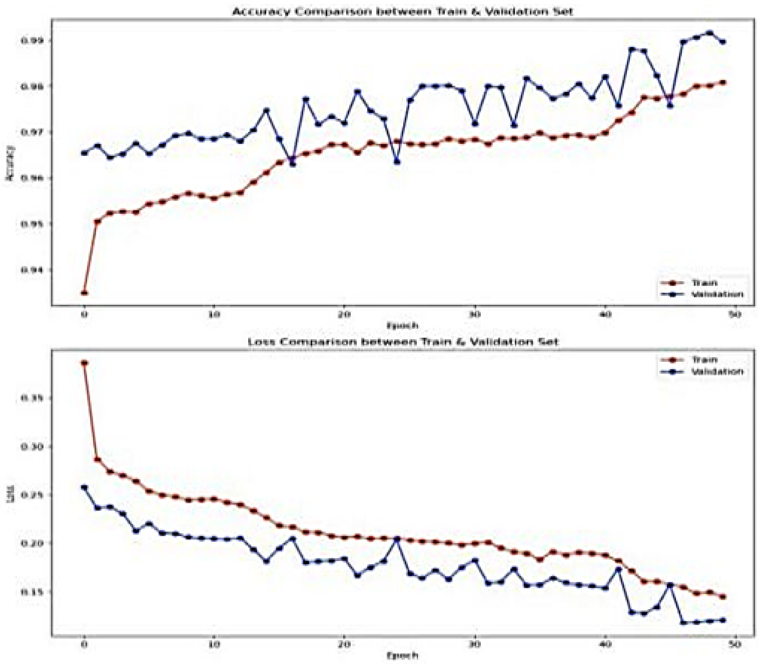

Figure 5 (A) Accuracy comparison between training and validation sets. (B) Loss comparison between training and validation sets.

Table 1 summarizes the detailed classification metrics for each category. These results validate the model's robustness in distinguishing between multiple stages of AD and healthy controls.

Table 1 Classification report of the CNN model across all categories.

Class	Precision	Recall	F1-score	Support
Mild Demented (0)	0.98	0.99	0.99	2250
Moderate Demented (1)	1.00	0.99	0.99	2250
Non-Demented (2)	0.99	1.00	0.99	2250
Very Mild Demented (3)	0.99	0.98	0.99	2250
Healthy (4)	0.99	0.99	0.99	2250
Accuracy			0.99	11250
Macro avg	0.99	0.99	0.99	11250
Weighted avg	0.99	0.99	0.99	11250

The Adam optimizer with a learning rate of 0.001 was found to be the most effective among the tested optimizers (SGD, RMSprop, Nadam), yielding an overall classification accuracy of 99%.

The integration of color-space transformations and aggressive data augmentation contributed significantly to this performance by enhancing feature discrimination and reducing overfitting. These findings support the viability of CNN-based MRI analysis as a diagnostic aid for early detection and progression monitoring of AD. The methodology demonstrated here may be generalized to other neuroimaging-based classification tasks in clinical decision support systems.

6 Conclusion

This study presents a CNN-based framework for multi-stage classification of Alzheimer's disease (AD) using MRI data. The model integrates convolutional layers, data augmentation, and color-space transformations to achieve a classification accuracy of 99% across five diagnostic categories. Among the evaluated optimizers, Adam with a learning rate of 0.001 demonstrated superior performance. The results highlight the potential of deep learning in supporting early and accurate AD diagnosis through non-invasive imaging. The proposed methodology offers a scalable, data-driven approach that may be extended to other neurodegenerative conditions. Future work will explore the integration of transfer learning to reduce training time and improve generalization, particularly across diverse demographic groups. Embedding this model into clinical decision-support systems could further enable early intervention and longitudinal patient monitoring in real-world healthcare settings.

References

[1] H. Davtyan, A. Ghochikyan, M. Mkrtichyan, N. Movsesyan, I. Petrushina, D. H. Cribbs, and M. G. Agadjanyan. Exploiting prime-boost regimen and various delivery strategies to improve Alzheimer's disease DNA vaccine efficacy. *Alzheimer's & Dementia*, 6(4):S591–S591, 2010.

[2] K. Ntalianis, G. Vachtsevanos, P. Borne, and A. Croitoru. Software solution incorporating activation cognitive memory portion in early stages of Alzheimer's disease. In *Applied Physics, System Science and Computers III*, volume 574, pages 74–80. Springer, 2019.

[3] P. Wang, Q. Zhao, Y. Zhou, Z. Hong, Q. Guo, and J. Liu. Emotional comparison between semantic dementia and Alzheimer's disease. *Frontiers in Psychiatry*, 12:680332, 2021.

[4] D. Melchiorri, S. Merlo, B. Micallef, J.-J. Borg, and F. Dráfi. Alzheimer's disease and neuroinflammation: Will new drugs in clinical trials pave the way to a multi-target therapy? *Frontiers in Pharmacology*, 14:1196413, 2023.

[5] Y. Wang, F. Pan, F. Xie, R. He, and Q. Guo. Correlation between urine formaldehyde and cognitive abilities in the clinical spectrum of Alzheimer's disease. *Frontiers in Aging Neuroscience*, 14:820385, 2022.
[6] J. R. Colca and B. N. Finck. Metabolic mechanisms connecting Alzheimer's and Parkinson's diseases: Potential avenues for novel therapeutic approaches. *Frontiers in Molecular Biosciences*, 9:929328, 2022.
[7] M. Moraghebi, R. Maleki, M. Ahmadi, A. A. Negahi, H. Abbasi, and P. Mousavi. In silico analysis of polymorphisms in microRNAs deregulated in Alzheimer disease. *Frontiers in Neuroscience*, 15:631852, 2021.
[8] K. Swakowska and A. Staniszewska. Alzheimer's disease: Classification and diagnosis criteria. *Journal of Education, Health and Sport*, 11(7):22–29, 2021.
[9] W. Ning-yu, Y. Hui-jie, S. Jing-fei, K. Feng, Z. Ming-xia, D. Hui-qing, Z. Xin-qing, J. Jian-ping, and D.-m. Han. Hearing impairment in senile dementia of Alzheimer's type. *Journal of Otology (Beijing)*, 2(1):14–17, 2007.
[10] S. Nocera, H. Telser, and D. Bonato. *The contingent valuation method in health care: An economic evaluation of Alzheimer's disease*. Springer, New York, 2003.
[11] M. Zimmermann. *The poetics and politics of Alzheimer's disease life-writing*. Palgrave Macmillan, Springer International Publishing, 2017.
[12] K. Nahar, X. Huang, M. H. Hossen, M. S. Rana, M. H. Kabir, and M. J. Islam. 3D human pose estimation via deep learning methods. Zenodo, 2023. https://doi.org/10.5281/zenodo.8120785
[13] S. Basaia, G. Agosta, E. Wagner, M. Canu, A. Magnani, F. Santangelo, et al. Automated classification of Alzheimer's disease and mild cognitive impairment using structural MRI with feature-based analysis and deep learning. *NeuroImage: Clinical*, 21:101645, 2019.
[14] J. Zhang, J. Liu, and B. Shen. Alzheimer's disease diagnosis based on multi-modal neuroimaging data using convolutional neural networks. *Frontiers in Neuroscience*, 13:509, 2019.
[15] I. S. Rahat, A. S. Miazee, and M. M. R. Emon. Deep learning-based FLAIR anomaly segmentation in brain MRI using EfficientNet and U-Net architectures. *IEEE Access*, 11:10598–10610, 2023.

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Analysis of the Influence of Parameters on Anomaly Detection Models of PyCaret

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Abstract

Anomaly detection plays a vital role in domains such as fraud prevention, medical diagnostics, and network security by identifying data points that deviate from normal patterns. PyCaret, a Python-based machine learning library, offers multiple unsupervised models for anomaly detection. This study evaluates the performance of five PyCaret models—K-Nearest Neighbours, Isolation Forest, Local Outlier Factor, Cluster-Based Local Outlier Factor, and Histogram-Based Outlier Detection—on a publicly available financial transaction dataset. Among these, the Isolation Forest model performed best and was further analysed for the effect of its *contamination* parameter. Varying the contamination parameter from 0.01 to 0.1 revealed that model performance improves when this threshold is set based on the statistical distribution of outliers in the dataset.

Keywords: Anomaly detection, unsupervised learning models, Isolation Forest, PyCaret, contamination parameter.

River Journal, 43–51.

1 Introduction

Anomaly detection refers to identifying data points that deviate significantly from the majority—often called outliers [1]. In many traditional classification tasks, such data are filtered out as noise, whereas anomaly detection specifically focuses on uncovering such rare and informative events. Its relevance spans diverse domains including fraud detection, network intrusion, medical diagnostics, and industrial quality control. For example, anomaly detection helps flag suspicious transactions in financial systems, detect abnormal ECG or EEG patterns in healthcare [2], and identify manufacturing defects. Machine learning techniques for anomaly detection are broadly categorized into supervised, semi-supervised, and unsupervised methods [1]. Supervised models require labeled data and perform well when anomalies are well-defined. However, in real-world applications, such labels are often unavailable. Semi-supervised models are trained on normal data and flag deviations during inference. Unsupervised models, requiring no labels, analyse the structure of the data and assign anomaly scores to each instance, making them ideal for unknown or evolving scenarios.

PyCaret [3] is a low-code Python library that simplifies machine learning workflows and supports several unsupervised anomaly detection algorithms. In this study, five commonly used PyCaret models are evaluated and compared: Isolation Forest, K-Nearest Neighbours, Local Outlier Factor, Cluster-Based Local Outlier Factor, and Histogram-Based Outlier Score. Isolation Forest (iForest) [4] isolates anomalies through recursive data partitioning. Anomalous instances, which are easier to isolate, result in shorter paths in the isolation tree. K-Nearest Neighbours (KNN) [6], although typically supervised, can be adapted for unsupervised anomaly detection by computing distances to neighbouring points—larger distances often indicating anomalies. Local Outlier Factor (LOF) [5] compares the local density of each point with its neighbours; low-density points receive high LOF scores and are treated as outliers. Cluster-Based LOF (CBLOF) [7] involves clustering the data and assigning anomaly scores based on intra- and inter-cluster distances, distinguishing between small and large clusters. Histogram-Based Outlier Score (HBOS) [8] models the distribution of each feature using histograms and assumes feature independence. It identifies outliers based on unusually low-frequency combinations. This study compares these models on publicly available fraud datasets and further investigates the effect of the contamination parameter on the Isolation Forest model.

As this parameter controls the threshold that separates normal data from anomalies, its tuning is essential for reliable detection.

2 Literature Review

Anomaly detection has been widely explored using supervised, semi-supervised, and unsupervised machine learning approaches. Belavagi and Muniyal [9] evaluated the performance of various supervised learning algorithms for intrusion detection and found that Random Forest achieved the highest accuracy. Alsulaiman and Al-Ahmadi [10] compared supervised and unsupervised methods, concluding that supervised models generally yield better performance in terms of accuracy. Krsteski et al. [11] investigated deep learning models such as CNN, RNN, DNN, and CNN–RNN hybrids using the CICIDS 2017 dataset and reported that CNN achieved the highest anomaly detection accuracy of 98.75%. Salim and Oughdir [12] evaluated deep learning techniques for detecting DoS attacks in wireless sensor networks, highlighting the superior capabilities of such models in complex detection scenarios. Hilal et al. [13] presented a review of anomaly detection techniques for financial fraud and discussed modern trends and challenges in the field. Pourhabibi et al. [14] focused on graph-based anomaly detection, conducting a systematic review using metrics such as processing time, precision, recall, accuracy, and F1-score. Quincozes et al. [15] demonstrated that supervised models outperformed unsupervised ones for blackhole attack detection, with the REPTree classifier achieving the highest F1-score. Lee et al. [16] applied the Isolation Forest algorithm with hyperparameter tuning to detect anomalies in storage batteries, showing that the method was both efficient and scalable. Olaniyan and Owoseni [17] conducted a comparative analysis of PyCaret's unsupervised anomaly detection models and the WHO's Data Quality Review (DQR) toolkit using HIV/AIDS datasets from Africa. Their study suggests that integrating anomaly detection tools with DQR can significantly enhance Data Quality Assessment (DQA) processes.

3 Methodology

As discussed in the literature, supervised learning algorithms tend to perform well in terms of accuracy. However, anomalies are often unknown and previously unseen in real-world applications such as fraud detection.

In such cases, supervised models alone may not be sufficient, and there arises a need to adopt unsupervised anomaly detection techniques. However, the parameters used significantly affect the performance of these unsupervised models. This study focuses on analyzing the influence of the contamination parameter, which plays a key role in determining the threshold for classifying a data point as normal or anomalous. PyCaret is chosen for implementation because it is an open-source, Python-based machine-learning library that simplifies the experimentation process. It provides access to several unsupervised anomaly detection models and allows users to perform end-to-end modeling with minimal coding. Although anomaly detection has several real-life applications, this work focuses specifically on fraud detection due to its importance in mitigating financial losses. The objective of the study is to analyze the behavior of anomaly detection models when their parameters are varied. The analysis is not tied to a specific dataset, and two publicly available datasets have been used for experimentation: a financial transactions dataset and a credit card transactions dataset, both sourced from Kaggle. A subset of 15,000 samples was taken from the financial transactions dataset, which includes fields such as transaction amount, transaction time, transaction ID, terminal ID, and a fraud indicator. The credit card transactions dataset contains one million samples and consists of features such as distance from home, distance from the last transaction, ratio to median purchase, repeat retailer, used chip, used pin number, and online order, along with a label indicating whether the transaction was fraudulent. The first three features are categorical, and the rest are binary. All the datasets used in this study are imbalanced, with a significantly lower number of fraudulent samples than normal ones. PyCaret automatically handles missing values during the setup phase, and no missing values were found in the datasets used. It also provides an option to ignore features that are not relevant to the modeling process. In this work, the fraud label was excluded during training as it is not required for unsupervised models. The anomaly detection module in PyCaret is designed to identify rare or suspicious events that significantly deviate from normal patterns. It includes built-in preprocessing capabilities that are applied during the setup. The modeling process includes setting up the environment, training the model, assigning anomaly labels, analyzing model performance, predicting anomalies on new data, and saving the final model. Each data point receives an anomaly score and a binary label, where ‘1’ indicates an anomaly and ‘0’ indicates a normal data point. These outputs are used to evaluate the effect of varying the contamination parameter on model performance.

Table 1 Comparison of various unsupervised models.

Model	Anomalous (Train)	Anomalous (Test)	Accuracy (%)
Isolation Forest	85,500	4,473	94.2
K-Nearest Neighbours	85,500	4,583	91.6
Local Outlier Factor	85,500	5,384	72.6
Cluster-Based Local Outlier	85,500	4,359	96.9
Histogram-Based Local Outlier	72,497	3,797	89.8

4 Results and Discussion

The anomaly detection models implemented using PyCaret include Isolation Forest, K-Nearest Neighbours, Local Outlier Factor, Cluster-Based Local Outlier Factor, and Histogram-Based Local Outlier Detection. All these models are based on unsupervised learning. In this study, 95% of the data was used for training and 5% was reserved for testing. Though these models do not rely on labeled data, the split was done to evaluate their performance on unseen data. All models were tested with the contamination parameter fixed at 0.09, and the rest of the parameters were left at default values. The credit-card transaction dataset consisted of 1,000,000 records, out of which 950,000 samples were used for training and 50,000 for testing. Among the test samples, 4,228 were anomalous, and the training set contained 83,115 anomalies. The number of anomalous samples identified and the corresponding accuracy for each model are presented in Table 1. From Table 1, it is observed that the Cluster-Based Local Outlier model provided the best accuracy at 96.9%, followed closely by Isolation Forest at 94.2%. However, the performance of the cluster-based model is sensitive to the number of clusters (k), and incorrect settings may degrade accuracy. A similar dependency on k exists in the K-Nearest Neighbours and Local Outlier Factor models. In contrast, the Histogram-Based model was less effective when the number of anomalies was small. Owing to its robustness and popularity in the literature, the Isolation Forest model was chosen for further analysis. In the second phase of the experiments, the behaviour of Isolation Forest was studied by varying the contamination parameter from 0.01 to 0.1 while keeping other parameters at default values [4]. This parameter determines the fraction of data expected to be anomalous and is used internally to compute a threshold based on the anomaly scores. For example, a contamination value of 0.05 implies that 5% of the data are assumed to be outliers. The fraudulent transaction dataset containing 15,000 records was used, with 5% of the data allocated for testing. The following performance metrics were computed:

Table 2 Accuracy for varying contamination parameter values of Isolation Forest.

Contamination	**Accuracy (Train)**	**Accuracy (Test)**
0.01	90.07	88.93
0.03	89.18	89.18
0.05	86.69	87.87
0.07	91.13	88.90
0.09	95.50	95.40

- **True Positive (TP)**: actual fraud correctly predicted as fraud.
- **True Negative (TN)**: normal data correctly predicted as normal.
- **False Positive (FP)**: normal data incorrectly predicted as fraud.
- **False Negative (FN)**: fraud data incorrectly predicted as normal.

The standard performance metrics used in evaluating model effectiveness include accuracy, precision, recall, and the F1 score. Accuracy, given in Eq. (1), measures the proportion of correctly classified instances out of all instances. Precision (Eq. (2)) indicates the fraction of correctly identified frauds among all predicted frauds. Recall, as expressed in Eq. (3), measures the ability of the model to detect actual fraudulent transactions. The F1 Score, shown in Eq. (4), is the harmonic mean of precision and recall, providing a balanced metric that is particularly useful for imbalanced datasets.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1 Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

Although accuracy provides a general overview of performance, it is not suitable for imbalanced datasets. Hence, metrics like precision, recall, and F1 score were also considered. The accuracy for various contamination values is shown in Table 2. Detailed performance metrics for the Isolation Forest model on test and training data are provided in Tables 3 and 4. As observed from the tables, the accuracy and F1 score are highest when the contamination parameter is set to 0.09.

Table 3 Performance metrics for Isolation Forest on test data.

Cont.	TP	TN	FP	FN	Recall	Precision	F1 Score	Accuracy
0.01	537	11948	888	878	37.95	37.60	37.5	88.93
0.03	331	12379	97	1444	16.70	77.30	27.8	89.18
0.05	499	12281	713	1254	28.40	41.10	33.5	87.87
0.07	805	12296	193	957	45.70	80.60	60.2	88.90
0.09	1207	12413	72	559	68.30	94.30	79.2	95.40

Table 4 Performance metrics for Isolation Forest on training data.

Cont.	TP	TN	FP	FN	Recall	Precision	F1 Score	Accuracy
0.01	43	624	26	57	43.00	62.30	50.7	90.07
0.03	13	656	3	78	14.30	81.25	23.8	89.18
0.05	30	629	14	77	28.03	68.10	39.6	86.69
0.07	33	634	12	71	31.70	73.33	43.5	91.13
0.09	69	647	3	31	69.00	95.83	80.0	95.50

The dataset used contains approximately 12% anomalies, which aligns closely with the best-performing contamination value. This suggests that the optimal setting of the contamination parameter can significantly improve the detection capability of the model, especially when aligned with the actual proportion of outliers in the dataset.

5 Conclusion

This study presented a comparative analysis of unsupervised anomaly detection models available in PyCaret, with a specific focus on their performance in fraud detection scenarios. Among the models evaluated, the Isolation Forest model exhibited consistently high accuracy and was further explored to assess the effect of varying the contamination parameter. The results demonstrated that the model performs optimally when the contamination parameter is aligned with the statistical distribution of outliers in the dataset. This highlights the importance of tuning the contamination parameter based on the expected proportion of anomalies, particularly in imbalanced datasets. For real-world applications where dataset characteristics may not be explicitly known, prior statistical knowledge or estimation techniques could guide parameter selection. As part of future work, additional parameters of the Isolation Forest model will be examined, and experiments will be extended to larger and more diverse datasets. Given the wide-ranging applications of anomaly detection, future studies will also consider domain-specific datasets to evaluate model behaviour across different contexts.

References

[1] M. Goldstein and S. Uchida. A comparative evaluation of unsupervised anomaly detection algorithms for multivariate data. *PLOS ONE, 11(4), 2016.*

[2] M. Radhakrishnan, S. Boruah, and K. Ramamurthy. EEG-based anomaly detection for autistic kids – a pilot study. Traitement du Signal, 39(3):1005–1012, 2022.

[3] M. Ali. PyCaret: An open source, low-code machine learning library in Python, 2020.

[4] F. T. Liu, K. M. Ting, and Z.-H. Zhou. Isolation Forest. In *Proceedings of the IEEE International Conference on Data Mining, Beijing, China, 2008.*

[5] M. M. Breunig, H.-P. Kriegel, R. T. Ng, and J. Sander. LOF: Identifying density-based local outliers. In Proceedings of the ACM SIGMOD International Conference on Management of Data, pages 93–104, 2000.

[6] G. Guo, H. Wang, D. Bell, Y. Bi, and K. Greer. KNN model-based approach in classification. In *Lecture Notes in Computer Science, vol. 2888. Springer, Berlin, Heidelberg, 2003.*

[7] Z. He, X. Xu, and S. Deng. Discovering cluster-based local outliers. Pattern Recognition Letters, 24(9–10):1641–1650, 2003.

[8] M. Goldstein and A. Dengel. Histogram-based outlier score (HBOS): A fast unsupervised anomaly detection algorithm. In *KI 2012, Poster and Demo Track, pages 59–63, 2012.*

[9] C. M. Belavagi and B. Muniyal. Performance evaluation of supervised machine learning algorithms for intrusion detection. Procedia Computer Science, 89:117–123, 2016.

[10] L. Alsulaiman and S. Al-Ahmadi. Performance evaluation of machine learning techniques for DoS detection in wireless sensor network. *International Journal of Network Security & Its Applications, 13(2):21–29, 2021.*

[11] S. Krsteski, M. Tashkovska, B. Sazdov, L. Radojichikj, A. Cholakoska, and D. Efnusheva. Intrusion detection with supervised and unsupervised learning using PyCaret over CI-CIDS 2017 dataset. In Lecture Notes in Networks and Systems, vol. 724. Springer, Cham, 2023.

[12] S. Salim and L. Oughdir. Performance evaluation of deep learning techniques for DoS attacks detection in wireless sensor network. *Journal of Big Data, 10(17), 2023.*

[13] W. Hilal, S. A. Gadsden, and J. Yawney. Financial fraud: A review of anomaly detection techniques and recent advances. Expert Systems with Applications, 193, 2022.

[14] T. Pourhabibi, K.-L. Ong, B. H. Kam, and Y. L. Boo. Fraud detection: A systematic literature review of graph-based anomaly detection approaches. *Decision Support Systems, 133, 2020.*

[15] S. E. Quincozes, J. F. Kazienko, and V. E. Quincozes. An extended evaluation on machine learning techniques for denial-of-service detection in wireless sensor networks. Internet of Things, 22, 2023.

[16] C.-H. Lee, X. Lu, X. Lin, H. Tao, Y. Xue, and C. Wu. Anomaly detection of storage battery based on isolation forest and hyperparameter tuning. In *Proceedings of the International Conference on Mathematics and Artificial Intelligence, ACM, New York, pages 229–233, 2020.*

[17] F. M. A. Olaniyan and A. Owoseni. Toward improved data quality in public health: Analysis of anomaly detection tools applied to HIV/AIDS data in Africa. In Proceedings of the IST-Africa Conference, Ireland, pages 1–9, 2022.

[18] S. Singh. Fraudulent transaction detection. Available: `https://www.kaggle.com/datasets/sanskar457/fraud-transaction-detection`, Accessed: Jul. 12, 2023.

[19] D. Narayanan R. Credit card fraud analysis. Available: `https://www.kaggle.com/datasets/dhanushnarayananr/credit-card-fraud`, Accessed: Jul. 12, 2023.

Biography

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Manufacturing of Stabilised Mud Blocks Reinforced with Jute fiber for Sustainable Construction

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Abstract

Stabilized mud blocks are increasingly recognized as eco-friendly alternatives to traditional bricks, offering reduced environmental impact through the use of locally available soil. This study evaluates the mechanical performance and durability of mud blocks reinforced with bidirectional jute fiber and stabilized with varying lime contents. The blocks were fabricated using a remote-operated compression device and tested for compressive strength, flexural tensile strength, and water absorption. Optimal results were observed at 8–10% lime content, with a 3-day compressive strength of 4.47 MPa, flexural tensile strength of 0.16 MPa, and 24-hour water absorption of 4.69%. The combination of lime and jute fiber notably improved strength, moisture resistance, and long-term durability. These findings support the adoption of fiber-reinforced, lime-stabilized mud blocks in sustainable construction practices.

Keywords: Stabilised mud blocks, jute fiber reinforcement, lime stabilization, compressive strength, flexural strength, water absorption, sustainable construction.

River Journal, 52–60.

1 Introduction

In the context of sustainable construction, compressed earth blocks (CEBs), rammed earth blocks, and mud blocks are gaining traction as eco-friendly alternatives to conventional materials. These methods utilize locally available soil and natural additives to minimize embodied energy, reduce carbon emissions, and lower construction costs. Mud blocks, in particular, eliminate the need for high-temperature firing, thereby significantly reducing energy consumption. Typically composed of soil, clay, and sand, they are stabilized using lime or cement and compacted into molds. Studies have also examined the effects of supplementary materials like fly ash and ground granulated blast furnace slag (GGBS) on the performance of lime-stabilized mud blocks [1]. This process lowers environmental impact, conserves natural resources, and supports local economies through decentralized production. Previous studies have explored stabilization techniques using microbial agents [2], hybrid mud-concrete compositions [3], and alternative binders such as alkali-activated industrial waste [4]. Kamal [5] emphasized the increasing adoption of compressed earth blocks as a sustainable alternative in low-energy construction.

The addition of natural fibers such as jute, coir, and palm has been shown to enhance mechanical performance by improving soil cohesion, tensile resistance, and crack control. fiber geometry, particularly the aspect ratio, has been shown to significantly influence the strength behavior of soil-based blocks [6]. These fibers also align with sustainability goals due to their biodegradability and availability. Polymeric fiber reinforcement has also been explored as an alternative, with promising mechanical outcomes [7], though natural fibers are generally preferred for their eco-compatibility. Alternative stabilization approaches using recycled aggregates, such as crushed brick waste, have also shown promising results in similar applications [8]. With rising demand for cost-effective and environmentally sound housing solutions, stabilized mud block technology presents a viable path for rural and urban development alike. Prakash et al. [9] have examined the viability of stabilized mud blocks in regional construction, supporting their relevance in affordable, resource-efficient housing. This study focuses on the manufacture and performance evaluation of jute fiber-reinforced mud blocks stabilized with lime, targeting improved compressive strength, flexural behavior, and moisture resistance.

2 Materials and Methods

2.1 Materials

Locally available soil was collected from a depth of 1 m in northern Hassan, Karnataka. Basic geotechnical tests were conducted as per IS 2720 to assess the suitability of the soil. The key properties are listed in Table 1.

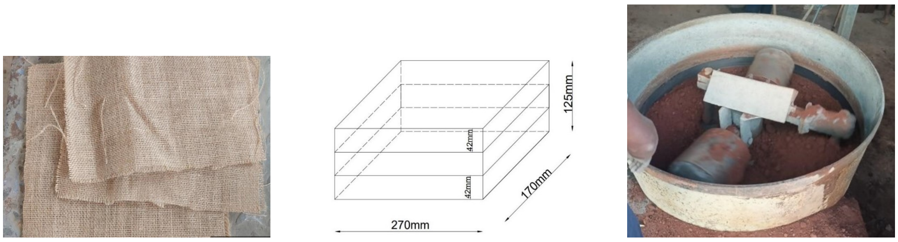
Table 1 Geotechnical properties of the soil

Property	**Value**
Specific gravity	2.59
Bulk density	2590 kg/m^3
Liquid limit	6.6%
Plastic limit	17.4%
Maximum dry density	1.76 g/cm^3

Soil type and composition are known to significantly influence block performance, as established by Mahendran and Vignesh [10], highlighting the importance of local soil characterization. Commercially available hydrated lime was used as a stabilizer at three dosage levels: 8%, 10%, and 12% by weight. Natural jute fibers (22 cm $\times$ 15 cm) were incorporated in two bidirectional layers per block, spaced 42 mm apart. These fibers provided tensile reinforcement and resistance to shrinkage cracks. Similar applications of natural and synthetic fibers have demonstrated improvements in strength, ductility, and durability of earth-based materials [11, 12].

2.2 Block Preparation

The dry mix of soil and lime was blended in a mechanical pan mixer, followed by the addition of 12% water. The mixture was placed into steel moulds (270 mm $\times$ 170 mm $\times$ 125 mm), with fiber mats inserted at specified depths. Blocks were compacted using a remote-operated hydraulic press exerting 3000 psi. After demoulding, they were cured for 7, 14, and 28 days under moist conditions. The effectiveness of compaction and curing has been shown to vary significantly with initial molding moisture content, as discussed by Kandasamy and Rachel [13], underscoring the need for consistent water control during fabrication.



(a) Jute fiber mats (b) Mould and fiber layout (c) Mixing and compaction setup

Figure 1 Materials and manufacturing process

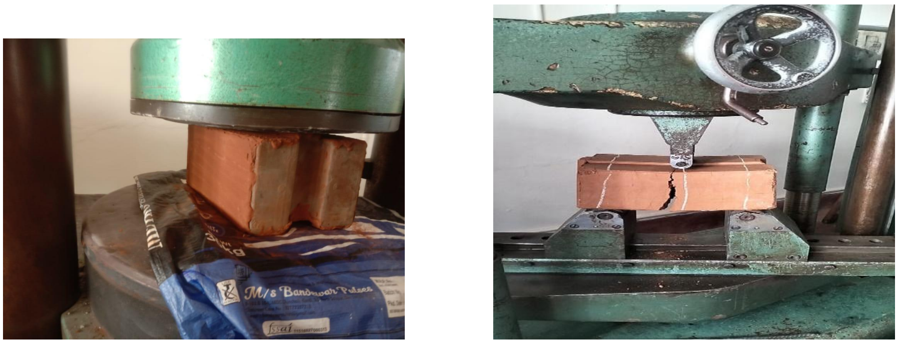
2.3 Testing Procedure

Three standard tests were conducted to assess the mechanical and durability properties of the stabilized mud blocks: compressive strength, flexural tensile strength, and water absorption. Compressive strength was evaluated using a Universal Testing Machine (UTM) following IS 3495 (Part 1):1992. Block samples were tested after 3 days of curing under both dry and wet conditions to assess strength retention under moisture exposure.

Flexural tensile strength was determined using a three-point bending setup in line with ASTM C1609. The modulus of rupture was calculated from bending loads recorded during testing, with results used to evaluate tensile resistance contributed by jute fiber reinforcement. Water absorption was measured after 24 hours of immersion, as per IS 3495 (Part 2):1976. The blocks were oven-dried, weighed, soaked in water, and reweighed to determine the percentage mass gain. All tests were conducted under controlled laboratory conditions with consistent moisture levels and specimen dimensions. Figure 2 shows a summary of the testing setups.

3 Results and Discussion

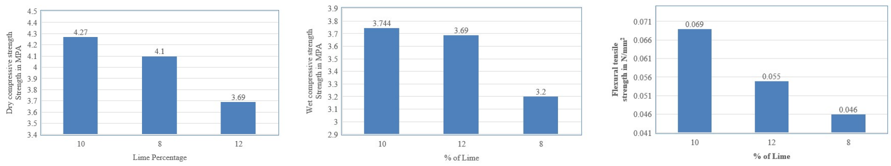
The compressive strength of the mud blocks increased with lime content up to 10%, after which a decline was observed. As shown in Figure 3(a), the highest dry compressive strength of 4.27 MPa was recorded at 10% lime, compared to 4.10 MPa at 8% and 3.69 MPa at 12%. A similar trend was observed under wet conditions, with a peak strength of 3.744 MPa at 10% lime, as shown in Figure 3(b). The results confirm that excessive lime content leads to over-stabilization, reducing cohesion and mechanical performance.



(a) Compressive testing (b) Flexural setup

Figure 2 Testing procedures for compressive strength and flexural tensile strength

Flexural tensile strength results (Figure 3(c)) showed a comparable trend. The inclusion of jute fibers, combined with lime stabilization, contributed to crack resistance and increased tensile capacity. The strength peaked at 0.069 N/mm^2 for 10% lime before declining to 0.055 N/mm^2 at 12%. This suggests that optimal tensile behavior is also achieved in the 8–10% lime range.



(a) Dry compressive strength (b) Wet compressive strength (c) Flexural tensile strength

Figure 3 Mechanical performance of mud blocks with varying lime content

Water absorption decreased with higher lime content, indicating improved matrix densification and reduced porosity due to pozzolanic reactions. The lowest absorption was recorded at 4.69% for 12% lime. While this suggests better moisture resistance at higher lime percentages, the corresponding loss in compressive and flexural strength supports 10% as the optimum content for balancing durability and mechanical integrity. Taallah and Guettala [14] similarly demonstrated that the combination of lime with natural fiber reinforcement enhances both mechanical strength and water resistance in compressed earth blocks.

These findings are consistent with the work of Arooz and Halwatura [3], who reported enhanced strength and durability in mud-concrete blocks with optimized stabilizer ratios. Ganesh et al. [11] also observed comparable improvements from fiber addition, reinforcing the effectiveness of natural fiber reinforcement in earthen construction.

4 Conclusion

This study demonstrated that jute fiber-reinforced mud blocks stabilized with lime offer improved mechanical strength and durability for sustainable construction. Optimal performance was observed at 10% lime content, yielding a dry compressive strength of 4.27 MPa, wet strength of 3.74 MPa, and flexural tensile strength of 0.069 N/mm^2. Water absorption was effectively reduced with increased lime, though mechanical properties declined beyond 10%. The integration of bidirectional jute fibers enhanced tensile resistance and crack control. These findings support the use of lime–fiber-stabilized mud blocks as viable, low-carbon alternatives in eco-conscious building applications. Future studies could explore long-term durability under varying climatic conditions and fiber orientation effects in scaled-up construction.

References

[1] N. Soundarya. Effect of fly ash and GGBS on lime stabilized mud block. *Materials Today: Proceedings, 47:4636–4640, 2021.*

[2] C. F. Arya, J. Augustine, H. Parengal, and A. D. Ravindran. Microbial geotechnology: Evaluation of strength and structural properties of microbial stabilized mud block (MSMB). International Journal of Scientific and Engineering Research, 7(1):278–282, 2016.

[3] F. Arooz and R. Halwatura. Mud-concrete block (MCB): Mix design and durability characteristics. *Case Studies in Construction Materials, 8:39–50, 2018.*

[4] K. Poorveekan, K. Ath, A. Anburuvel, and N. Sathiparan. Investigation of the engineering properties of cementless stabilized earth blocks with alkali-activated eggshell and rice husk ash as a binder. Construction and Building Materials, 277:122371, 2021.

[5] D. M. A. Kamal. Analyzing the potential of compressed earth blocks as a feasible and sustainable building material. *Architecture Engineering and Science, 8:39–50, 2024. Available:* `https://www.academia.edu/100836235`

[6] H. Danso, D. B. Martinson, M. Ali, and J. Williams. Effect of fiber aspect ratio on mechanical properties of soil building blocks. Construction and Building Materials, 83:314–319, 2015.

[7] N. P. Vignesh, N. Arunachelam, K. Mahendran, and B. D. Kumar. A study on polymeric fiber reinforced stabilized mud blocks. *IOP Conference Series: Materials Science and Engineering, 1026(1):012010, 2021.*

[8] P. Kasinikota and D. D. Tripura. Evaluation of compressed stabilized earth block properties using crushed brick waste. Construction and Building Materials, 280:122520, 2021.

[9] V. Prakash, A. S. Amal Raj, B. Mathew, and V. R. Sumith. Studies on stabilized mud block as a construction material. *International Journal of Innovative Research in Advanced Engineering, 3(1):19–24, 2016.*

[10] K. Mahendran and N. P. Vignesh. A study on the influence of soil properties and additives on the strength of mud blocks. International Journal of Applied Engineering Research, 10(53):1–7, 2015.

[11] C. Ganesh, J. Sumalatha, K. Sreekeshava, and K. Sharath. Experimental study on strength behaviour of geofiber reinforced stabilized mud blocks using industrial byproducts. *Materials Today: Proceedings, 2023.*

[12] M. A. D. M. Gokulakrishnan. Experimental investigation on stabilized mud blocks. International Journal of Engineering Research and Applications, 6:3486–3489.

[13] A. Kandasamy and P. P. Rachel. An experimental evaluation of the impact of moulding moisture content on the compressive strength of unstabilised compressed earth blocks. *E3S Web of Conferences, 387:04014, 2023.*

[14] B. Taallah and A. Guettala. The mechanical and physical properties of compressed earth block stabilized with lime and filled with untreated and alkali-treated date palm fibers. Construction and Building Materials, 104:52–62, 2016.

[15] S. Raj, S. Mohammad, R. Das, and S. Saha. Coconut fiber-reinforced cement-stabilized rammed earth blocks. *World Journal of Engineering, 14(3):208–216, 2017.*

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Hospital-Acquired Infection Management with Artificial Intelligence: A Comprehensive Review

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Abstract

Hospital-acquired infections (HAIs) remain a major contributor to patient morbidity, mortality, and healthcare costs. This review examines how artificial intelligence (AI) enhances HAI detection, surveillance, and management through models such as support vector machines, decision trees, and natural language processing. These techniques enable real-time risk prediction and support clinical decision-making. Key challenges including data privacy, system integration, and model interpretability are also discussed. The review highlights the need for ethical, interdisciplinary approaches and concludes that AI offers a promising shift from reactive to proactive infection control in modern healthcare systems.

Keywords: Hospital-Acquired Infections, Nosocomial Infections, Artificial Intelligence, Machine Learning, Intelligent Surveillance, Predictive Modelling, Clinical Decision Support.

River Journal, 61–70.

1 Introduction

Hospital-acquired infections (HAIs), also referred to as nosocomial infections, pose a persistent challenge to healthcare systems worldwide due to their significant impact on patient morbidity, mortality, and resource utilisation. These infections—such as urinary tract infections (UTIs), surgical site infections (SSIs), bloodstream infections, and ventilator-associated pneumonia—typically arise during hospitalisation and are not present or incubating at the time of admission [1]. They are often linked to invasive procedures, medical devices, or surgical interventions, and are caused by a wide range of pathogens, including bacteria, viruses, fungi, and parasites [2]. Traditional HAI surveillance methods, including manual chart reviews and laboratory reports, are limited by delays, subjectivity, and underreporting. Variability in clinical decision-making further complicates infection control efforts. The COVID-19 pandemic intensified these issues by introducing new transmission risks and straining healthcare infrastructure. In response, artificial intelligence (AI) has emerged as a transformative approach to infection surveillance and management. AI models—including support vector machines (SVMs), decision trees, neural networks, and natural language processing (NLP)—can process large-scale healthcare data in real time, enabling early identification of infection risks, predicting outbreak trends, and optimizing clinical resources. Notably, recent studies have reported AUROC values exceeding 90% for AI-based HAI prediction models [3], highlighting their potential for real-world deployment. Furthermore, AI-based training and monitoring systems (AITMS) have improved adherence to infection control protocols, such as the use of personal protective equipment (PPE), through continuous surveillance and feedback [4]. These systems can uncover patterns in complex datasets that may elude conventional analytical approaches, thereby facilitating personalised and proactive interventions. A comparative summary of conventional versus AI-based methods for HAI surveillance is presented in Table 1. A broader conceptual framework for AI-driven infection management, covering technologies, data sources, and stakeholders, is illustrated in Figure 1.

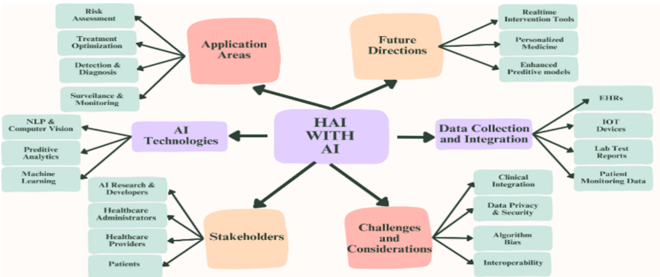

Figure 1 Overview of the study: Conceptual framework outlining AI applications for HAI management, including key stakeholders, technologies, data sources, and future directions.

Table 1 Comparison of traditional and AI-based methods for HAI surveillance

Aspect	**Traditional Methods**	**AI-based Methods**
Performance	Variability in sensitivity and specificity; generally modest detection rates	Higher sensitivity and specificity in identifying HAIs; demonstrated superior performance in some clinical settings [5]
Data Requirements	Manual data entry; prone to incompleteness and underreporting	Capable of processing large, complex datasets; reliant on quality of digitised records [6]
Timeliness	Often delayed due to retrospective review	Near real-time detection and intervention possibilities

2 Methodology

This review investigates the application of artificial intelligence (AI) models in predicting and managing hospital-acquired infections (HAIs) across healthcare environments. A structured literature review approach was adopted to ensure the inclusion of relevant and high-quality studies.

Inclusion Criteria

Peer-reviewed articles published from 2010 onwards were considered if they:

- Employed empirical methods for HAI prediction or management,
- Implemented AI or machine learning (ML) algorithms, and
- Reported model performance metrics such as accuracy, precision, recall, F1-score, or AUROC.

Exclusion Criteria

The following were excluded from the review:

- Non-empirical works (e.g., opinion pieces, editorials),
- Non-English publications, and
- Studies not explicitly addressing HAIs.

Research Objectives

The review aimed to answer the following research questions:

- **RQ1:** How effective are AI models in predicting HAIs across clinical settings?
- **RQ2:** Which AI techniques yield the best results, and under what conditions?
- **RQ3:** What are the key challenges in deploying AI models for HAI surveillance in real-world hospitals?

Search Strategy and Screening

Relevant literature was identified through keyword-based searches in PubMed, IEEE Xplore, Scopus, and Google Scholar. Search terms included combinations of "hospital-acquired infections," "nosocomial infections," "machine learning," "artificial intelligence," and "predictive modelling." Titles and abstracts were screened for relevance, followed by full-text reviews of selected articles. Data were extracted on algorithms used, datasets, evaluation metrics, and implementation context.

Scope of the Review

The review focuses on AI-enabled monitoring and infection control systems within hospital settings. Emphasis is placed on model performance, interpretability, and practical feasibility. Studies involving structured (e.g., electronic health records) and unstructured data (e.g., clinical notes) were included to capture the diversity of AI techniques in use.

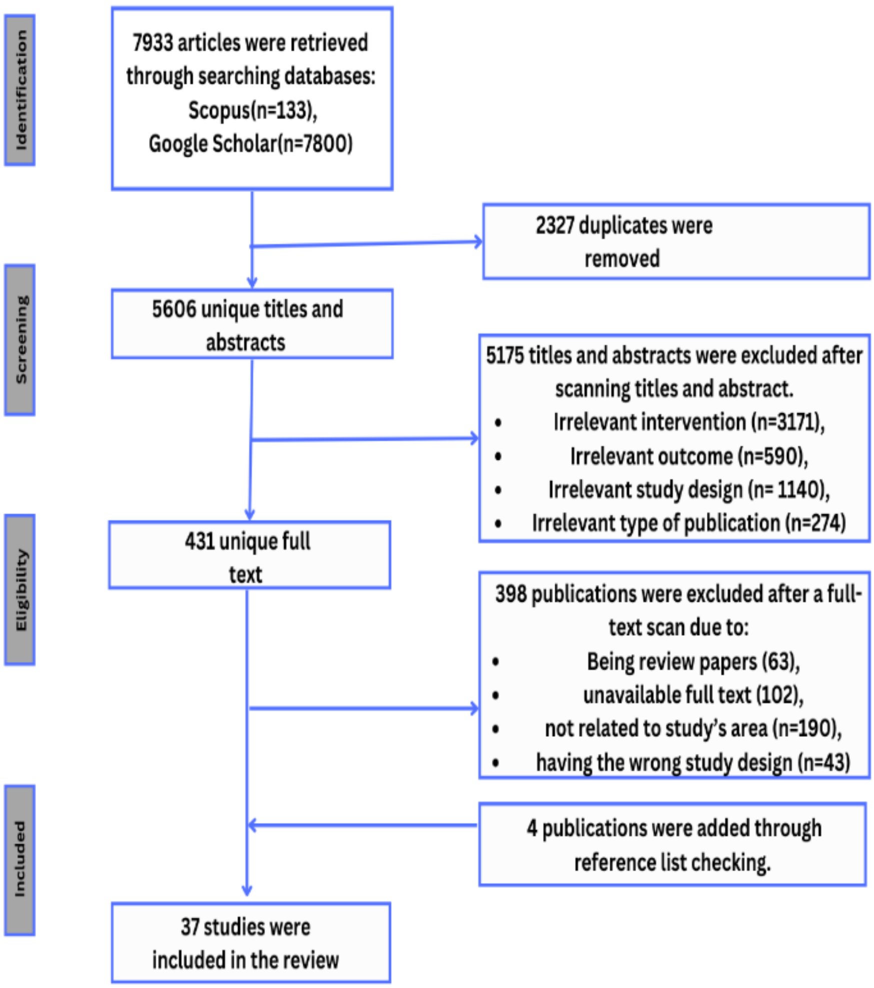

Figure 2 Systematic review methodology applied for literature selection

3 Results and Discussion

This section synthesises findings from selected studies on AI applications for the prediction, surveillance, and control of hospital-acquired infections (HAIs). The discussion is structured around the research questions outlined in the methodology.

RQ1: Efficiency of AI Models in Predicting HAIs

Numerous studies report that AI models outperform conventional approaches in HAI prediction. Ferreira et al. [7] employed random forest algorithms using over 200 NHSN-based features, achieving superior accuracy across diverse hospital datasets. Similarly, Ehrentraut et al. [5] demonstrated that gradient tree boosting achieved a recall of 93.7% and an F1-score of 85.7%, significantly surpassing traditional surveillance scores such as SAPS II. Support vector machines (SVMs) and ensemble techniques have been particularly effective in modelling nonlinear risk factors. For instance, Barchitta et al. [8] showed improved HAI identification using ICU admission data, while Branch-Elliman et al. [9] successfully applied natural language processing (NLP) to detect urinary tract infections from clinical narratives. These findings collectively affirm the high predictive capability of AI in clinical infection control.

RQ2: Effective AI Techniques and Their Contexts

Among the evaluated methods, SVMs with radial basis function (RBF) kernels, random forests, XGBoost, and decision trees emerged as consistent top performers. Ensemble methods, in particular, showed robustness across varied datasets—including structured EHRs, microbiological results, and clinical notes. Savin et al. [10] noted that XGBoost handled imbalanced and noisy datasets effectively. Moreover, studies emphasise the role of model optimisation: Ehrentraut et al. [5] demonstrated that simple preprocessing and hyperparameter tuning significantly enhanced model precision and recall, suggesting the importance of calibration over algorithm choice alone.

Table 2 Mapping of infection types to AI approaches and data characteristics

Infection Type	Key Data Features	Suitable AI Approaches
Urinary tract infections (UTIs)	Demographics, urinalysis, catheter use	Logistic regression, decision trees, ensemble models (random forest, XGBoost)
Surgical site infections (SSIs)	Surgical history, culture reports, wound classification	NLP on clinical notes + structured data via ensemble models
Ventriculitis and meningitis	CSF analysis, imaging, neurological markers	Tree-based models (random forest, XGBoost)
Catheter-associated infections	Insertion/removal logs, nursing notes, microbial tests	RNNs, LSTM for temporal data; Bayesian networks + NLP

Table 2 summarises key infection types with corresponding data characteristics and AI models. These mappings indicate that no universal model exists for all HAIs; model selection must align with clinical context and data availability.

RQ3: Challenges in Real-World Implementation

Despite strong performance in controlled studies, several barriers hinder AI integration in clinical environments. Matheny et al. [11] and Jiang et al. [12] highlight challenges such as data heterogeneity, lack of generalisability, and the "black box" nature of complex models, which limit interpretability and clinician trust. Privacy and data governance are critical concerns, particularly in deep learning applications where model logic is difficult to audit [13]. Integration with existing hospital information systems also presents technical challenges, requiring robust interoperability and cross-disciplinary collaboration [14]. Nonetheless, promising real-world use cases exist. Dos Santos et al. [3] applied a multilayer perceptron model that successfully identified 67 of 73 HAI cases in deployment, achieving high sensitivity. Their findings underscore the potential of AI for early detection, provided continuous model validation and clinical oversight are ensured.

4 Conclusion

This review highlights the growing relevance of artificial intelligence (AI) in hospital-acquired infection (HAI) prediction, surveillance, and control. Across various infection types and healthcare settings, AI models—including support vector machines (SVMs), decision trees, ensemble methods such as random forest and XGBoost, and deep learning techniques—have consistently outperformed traditional statistical approaches. These models effectively process structured data, clinical biomarkers, and unstructured notes to provide early, accurate risk identification and support evidence-based decision-making. However, several implementation challenges remain, including data fragmentation, limited model interpretability, and interoperability with hospital systems. Ethical concerns surrounding patient privacy and algorithmic transparency further complicate adoption. Future progress will depend on developing explainable AI systems, integrating predictive models into real-time hospital workflows, and designing unified frameworks capable of managing multiple HAI types through multi-modal learning.

Cross-disciplinary collaboration and continuous model validation are essential to ensure safe, effective, and sustainable deployment. With appropriate governance and clinical engagement, AI can transform infection control into a proactive, data-driven domain that improves patient outcomes and enhances healthcare efficiency.

References

[1] Khan, H. A., Baig, F. K., and Mehboob, R., "Nosocomial infections: Epidemiology, prevention, control and surveillance," *Asian Pacific Journal of Tropical Biomedicine*, vol. 7, no. 5, pp. 478–482, 2017. doi:10.1016/j.apjtb.2017.01.019.

[2] Koch, A. M., Nilsen, R. M., Eriksen, H. M., Cox, R. J., and Harthug, S., "Mortality related to hospital-associated infections in a tertiary hospital; repeated cross-sectional studies between 2004–2011," *Antimicrobial Resistance and Infection Control*, vol. 4, 2015. doi:10.1186/s13756-015-0097-9.

[3] Dos Santos, R. P., Silva, D., Menezes, A., Lukasewicz, S., Dalmora, C. H., Carvalho, O., et al., "Automated healthcare-associated infection surveillance using an artificial intelligence algorithm," *Infection Prevention in Practice*, vol. 3, no. 3, 2021. doi:10.1016/j.infpip.2021.100167.

[4] Huang, T., Ma, Y., Li, S., Ran, J., Xu, Y., Asakawa, T., and Lu, H., "Effectiveness of an artificial intelligence-based training and monitoring system in prevention of nosocomial infections: A pilot study of hospital-based data," *Drug Discoveries & Therapeutics*, vol. 17, no. 5, pp. 351–356, 2023. doi:10.5582/ddt.2023.01068.

[5] Ehrentraut, C., Ekholm, M., Tanushi, H., Tiedemann, J., and Dalianis, H., "Detecting hospital-acquired infections: A document classification approach using support vector machines and gradient tree boosting," *Health Informatics Journal*, vol. 24, no. 1, pp. 24–42, 2016. doi:10.1177/1460458216656471.

[6] Cosentino, C. B., Mitchell, B. G., Brewster, D. J., and Russo, P. L., "The utility of frailty indices in predicting the risk of health care associated infections: A systematic review," *American Journal of Infection Control*, vol. 49, no. 8, pp. 1078–1084, 2021. doi:10.1016/j.ajic.2020.12.001.

[7] Lukasewicz Ferreira, S. A., Franco Meneses, A. C., Vaz, T. A., da Fontoura Carvalho, O. L., Hubner Dalmora, C., Pressotto Vanni, D., et al., "Hospital-acquired infections surveillance: The machine-learning algorithm mirrors national healthcare safety network definitions," *Infection Control and Hospital Epidemiology*, 2024. doi:10.1017/ice.2023.224.

[8] Barchitta, M., Maugeri, A., Favara, G., Riela, P. M., Gallo, G., Mura, I., and Agodi, A., "A machine learning approach to predict healthcare-associated infections at intensive care unit admission: Findings from the SPIN-UTI project," *Journal of Hospital Infection*, vol. 112, pp. 77–86, 2021. doi:10.1016/j.jhin.2021.02.025.

[9] Branch-Elliman, W., Strymish, J., Kudesia, V., Rosen, A. K., and Gupta, K., "Natural language processing for real-time catheter-associated urinary tract infection surveillance: Results of a pilot implementation trial," *Infection Control and Hospital Epidemiology*, vol. 36, no. 9, pp. 1004–1010, 2015. doi:10.1017/ice.2015.122.

[10] Savin, M., Apollonio, L., Moretti, M., and Bertolini, M., "Decision support systems for hospital-acquired infection prediction: A comparative study of XG-Boost and logistic regression," *Artificial Intelligence in Medicine*, vol. 135, 2023. doi:10.1016/j.artmed.2023.102461.

[11] Matheny, M. E., Whicher, D., and Thadaney Israni, S., "Artificial intelligence in health care," *JAMA*, vol. 323, no. 6, pp. 509–510, 2020. doi:10.1001/jama.2019.21579.

[12] Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., et al., "Artificial intelligence in healthcare: Past, present and future," *Stroke and Vascular Neurology*, vol. 2, no. 4, pp. 230–243, 2017. doi:10.1136/svn-2017-000101.

[13] Denecke, K., and Baudoin, C. R., "A review of artificial intelligence and robotics in transformed health ecosystems," *Frontiers in Medicine*, vol. 9, 2022. doi:10.3389/fmed.2022.795957.

[14] Jung, J. S., "Current status and future direction of artificial intelligence in healthcare and medical education," *Korean Medical Education Review*, vol. 22, no. 2, pp. 99–114, 2020. doi:10.17496/kmer.2020.22.2.99.

Biography

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A Blockchain-Based Trusted and Traceable Framework for Donation Management

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Abstract

Traditional donation systems often face challenges related to transparency, accountability, and data security. This study explores how blockchain technology can address these limitations through decentralised, tamper-proof, and traceable transaction models. Drawing from case studies and comparative analysis, the paper highlights the benefits of smart contracts and data integrity in enhancing trust within charitable ecosystems. It also considers ethical aspects and the future potential of integrating artificial intelligence for smarter, more accountable donation frameworks.

Keywords: Blockchain, Donation Management, Charitable Contributions, Smart Contracts, Transparency, Data Security.

River Journal, 71–79.

1 Introduction

Effective donation management remains a persistent challenge in the non-profit sector, largely due to economic instability and limited donor bases. These organizations grapple with issues related to resource allocation, advocacy, and securing strategic funding. This paper investigates the role of blockchain technology in transforming donation management by promoting transparency, efficiency, and trust. While blockchain presents several advantages, concerns regarding privacy and institutional trust continue to warrant attention. Emerging models such as the Charity Chain employ smart contracts to address these challenges and rebuild public confidence in charitable systems. Recent research has examined the application of blockchain in various donation contexts, including organ and blood donation, traceability, and fraud prevention [1–9]. Table 1 presents a summary of blockchain advantages across different domains of donation management, highlighting its capacity to enhance integration, transparency, data security, and operational efficiency.

Table 1 Overview of Current Donation Management Systems

Aspect	Citations	Blockchain Advantage	Real-world Examples
Agile Value Chains and Integration	[10]	Accelerates product innovation and IoT/cloud integration	Agile digital supply chains
Addressing Socioeconomic Challenges	[11]	Tackles issues like financial inclusion and climate response	Strategic development initiatives
Security, Transparency, and Trust	[12, 13]	Decentralised, tamper-proof ledger increases trust	Walmart's food traceability blockchain
Immutability	[12, 14]	Ensures unalterable data records	Sweden's blockchain-based land registry
Smart Contracts	[12, 15]	Automates trustless execution and removes intermediaries	Ethereum and DeFi platforms
Decentralization	[12, 16]	Removes central authority, reducing control risks	Bitcoin network resilience
Efficiency and Cost Reduction	[12, 17]	Reduces transaction time and cost	Ripple's cross-border payments
Data Integrity	[12, 18]	Ensures cryptographically secure data	Estonia's healthcare blockchain
Tokenization	[12, 19]	Enables fractional ownership and liquidity	Tokenised real estate platforms

These insights suggest that blockchain can significantly strengthen donation ecosystems, albeit with ethical considerations. The discussion aims to guide decision-makers, policymakers, and researchers in leveraging blockchain for transparent and traceable charitable systems.

2 Methods

This study employs a systematic approach to evaluate the application of blockchain in donation management systems. The methodology includes a combination of literature review, case study analysis, and comparative evaluation.

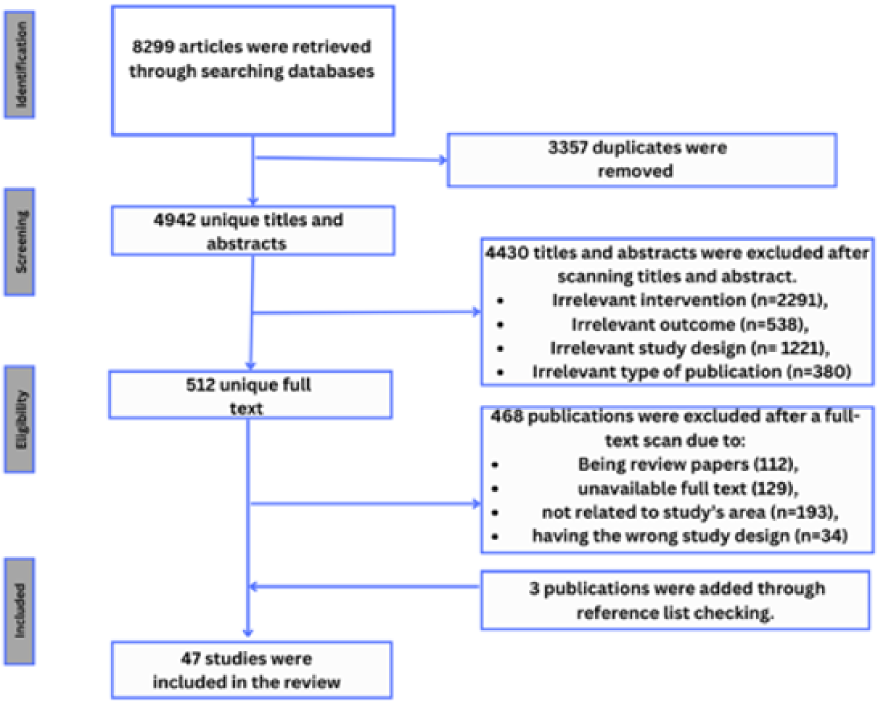

Figure 1 Flowchart showing inclusion criteria and screening process for reviewed articles.

Case studies of real-world blockchain implementations in charitable contexts were analysed to assess their practical viability. These revealed benefits such as transparency and reduced reliance on intermediaries, alongside challenges like user trust and integration.

A comparative analysis was conducted between blockchain-based and traditional platforms, focusing on workflow, transparency, and efficiency. Blockchain systems offered distinct advantages via automation and decentralised verification. Finally, insights from literature, case studies, and comparisons were synthesised to identify recurring patterns, challenges, and conceptual models in blockchain adoption for secure donation management.

3 Key Insights

Traditional donation methods face persistent challenges related to transparency, ethical clarity, and operational inefficiencies. These issues are particularly evident in areas such as living donor transplantation, where opaque processes undermine public trust. Blockchain technology offers a promising solution by enabling traceable, decentralised, and tamper-resistant systems for managing charitable transactions. Several studies have highlighted the limitations of current systems, emphasizing the lack of accountability and inefficiencies in reporting [4, 20]. Researchers suggest that blockchain can enhance transparency and confidentiality in donation processes through features such as smart contracts and immutable ledgers. However, concerns remain regarding ethical reporting, where procedural transparency may overshadow actual ethical outcomes [21]. To address privacy concerns, solutions like blockchain-based one-time account systems have been proposed to secure donor data [2, 3]. Such approaches aim to balance transparency with confidentiality, ensuring both security and ethical responsibility in donation systems. Blockchain further supports advanced models for Zakat and organ donation management by enabling secure traceability, preventing fraud, and automating recipient verification [22, 23]. For example, frameworks such as Blockchain-Based Donation Traceability (BBDT) and CharityCoin have been developed to increase donor engagement and system accountability [24, 25]. Applications like Global Sadaqah and blockchain-enabled blood donation systems demonstrate real-world viability. These platforms incorporate permissioned blockchains, real-time notifications, and identity verification to track and optimize resource allocation in healthcare and humanitarian contexts [26, 27]. Together, these insights demonstrate blockchain's potential to improve transparency, traceability, and ethical compliance across diverse charitable ecosystems.

4 Discussion

Blockchain-based platforms for charitable donations offer substantial advantages over traditional systems. Key benefits include enhanced transparency, traceability, data security, and operational efficiency. These features collectively help improve accountability and reduce the risk of fraud. Despite these advantages, several challenges persist. Notably, the reliance on cryptocurrencies, the need for technical expertise, and integration complexities may limit adoption among non-technical stakeholders. Donor hesitation may also arise from a lack of familiarity with decentralised systems. Ensuring privacy through encrypted, decentralised architectures and automating transactions via smart contracts can streamline fund distribution while eliminating intermediaries. However, striking the right balance between technological potential and practical implementation demands coordinated efforts from developers, donors, and institutions. Further interdisciplinary research is required to ensure that blockchain adoption in donation systems is both ethically sound and contextually appropriate. Understanding regulatory, social, and technological nuances is essential to developing robust, scalable, and trustworthy platforms across humanitarian domains.

5 Conclusion

This study highlights the transformative potential of blockchain technology in the domain of donation and philanthropy management. By addressing longstanding issues of transparency, traceability, and ethical accountability, blockchain offers a decentralised framework that can enhance trust and operational efficiency. The reduction of intermediaries, coupled with the use of smart contracts, allows for more secure, cost-effective, and auditable donation processes. The paper further outlines the applicability of blockchain in diverse contexts, including Zakat management, blood donations, and organ transplant systems. While the benefits are considerable, challenges such as implementation complexity, user awareness, and privacy concerns must be carefully addressed. Striking a balance between innovation and ethical compliance is crucial for ensuring widespread adoption and maintaining donor confidence. Looking ahead, the integration of artificial intelligence (AI) and machine learning (ML) into blockchain-enabled platforms offers exciting opportunities. Predictive analytics can optimise donor outreach, while anomaly detection systems can improve fraud prevention. AI can also personalise engagement and support real-time decision-making in fund allocation. Moreover, blockchain's support for tokenisation and smart contracts could enable new forms of non-monetary giving and cross-border transparency in donation systems. Continued interdisciplinary research is essential to refine these technologies and ensure they serve humanitarian goals effectively, ethically, and sustainably.

References

[1] N. H. Ab Samad, N. H. Ahmad, and K. Suria. Sustainability of non-profit organizations: A systematic review. *Accounting and Finance Research, 12(2):1–25, 2023.*

[2] *Y. C. Cho and H. Park. Financial sustainability of nonprofit organizations: Determinants of fundraising campaigns on donation intention.* The Journal of Industrial Distribution & Business, 11(3):19–28, 2020.

[3] J. Lee, A. Seo, Y. Kim, and J. Jeong. Blockchain-based one-off address system to guarantee transparency and privacy for a sustainable donation environment. *Sustainability, 10(12):4422, 2018.*

[4] *A. Seo, Y. Son, Y. Lee, and J. Jeong. Personal donation system using a blockchain for enhanced transparency.* Webology, 19(1):4761–4777, 2022.

[5] A. Weller. Transparency: Motivations and challenges. In *Explainable AI: Interpreting, Explaining and Visualizing Deep Learning, pages 23–40. Springer, Cham, 2019.*

[6] *N. S. Sirisha, T. Agarwal, R. Monde, R. Yadav, and R. Hande. Proposed solution for trackable donations using blockchain. In* Proc. 2019 Int. Conf. on Nascent Technologies in Engineering (ICNTE), pages 1–5, 2019.

[7] S. Lowell, L. Silverman, and L. Taliento. Not-for-profit management: The gift that keeps on giving. *The McKinsey Quarterly, page 147, 2001.*

[8] *I. Lapsley. Challenges to nonprofit organisations in a changing world. In* Funktionen und Leistungen von Nonprofit-Organisationen, pages 17–25. Springer, 2004.

[9] M. M. Islam. In-kind donation practices, challenges and strategies for NGOs and donors. Georgia Institute of Technology, 2013.

[10] A. G. Varghese and S. Amudha. Blockchain and its applications in various fields – a survey. *Journal of Mechanics of Continua and Mathematical Sciences, 1(2), 2019.*

[11] *B. Lopez, D. García, and A. Alcaide. Blockchain technology facing socioeconomic challenges. Promise versus probability. Sumy State University, 2019.*

[12] *W. Baiod, J. Light, and A. Mahanti. Blockchain technology and its applications across multiple domains: A survey.* Journal of International Technology and Information Management, 29(4):78–119, 2021.

[13] A. Sristy. Blockchain in the food supply chain. Walmart Global Tech, 2021. Available: `https://commerce.walmart.com`

[14] E. Haaramo. Sweden trials blockchain for land registry management. *Computer Weekly, 5 July 2017.*

[15] *F. Schär. Decentralized finance: On blockchain- and smart contract-based financial markets.* FRB of St. Louis Review, 2021.

[16] C. Gundiuc. Can government intervention stop Bitcoin? *BeInCrypto, 2019. Available: `https://beincrypto.com`*

[17] J. Tyrrell. Blockchain-based cross-border payments – the ripple effect. TechHQ, 2023.
[18] S. Malhotra, S. Chandak, and Sunita. What is Estonia doing with blockchain in providing healthcare to its citizens? *InnoHealth Magazine, 2021. Available:* `https://innohealthmagazine.com`
[19] A. Zunino. The future of real estate: Tokenization and its impact on the industry. Forbes, 22 May 2023. Available: `https://www.forbes.com`
[20] J. Jeong, D. Kim, Y. Lee, J.-W. Jung, and Y. Son. A study of private donation system based on blockchain for transparency and privacy. In *Proc. 2020 Int. Conf. on Electronics, Information, and Communication (ICEIC), pages 1–4.*
[21] N. Hyndman and D. McConville. Transparency in reporting on charities' efficiency: A framework for analysis. Nonprofit and Voluntary Sector Quarterly, 45(4):844–865, 2016.
[22] D. Hawashin et al. Blockchain-based management for organ donation and transplantation. *IEEE Access, 10:59013–59025, 2022.*
[23] D. Rejeb. Blockchain and smart contract's contributions to Zakat management system. In Proc. Indonesian Conference of Zakat, pages 15–24, 2020.
[24] A. Almaghrabi and A. Alhogail. Blockchain-based donations traceability framework. *Journal of King Saud University–Computer and Information Sciences, 34(10):9442–9454, 2022.*
[25] M. S. Farooq, M. Khan, and A. Abid. A framework to make charity collection transparent and auditable using blockchain technology. Computers & Electrical Engineering, 83:106588, 2020.
[26] D. Hawashin et al. Blockchain-based management of blood donation. *IEEE Access, 9:163016–163032, 2021.*
[27] S. Lakshminarayanan, P. N. Kumar, and N. M. Dhanya. Implementation of blockchain-based blood donation framework. In Proc. Int. Conf. on Computational Intelligence in Data Science, Springer, pages 276–290, 2020.

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Effect of Overcrowding on Seismic Performance of Elevation Irregular Medium Height Structures

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Abstract

Buildings are typically designed to resist prescribed dead, live, wind, and seismic loads. However, overloading—due to material misplacement or long-term use—can exceed design thresholds, especially in elevation-irregular structures. This study investigates the compounded seismic vulnerability caused by such overloading through three-dimensional nonlinear pushover analysis in ETABS. Two reinforced concrete frame types—regular and elevation-irregular—are analyzed with live loads ranging from 5 to 40 kN/m^2. The results indicate that live load increases amplify roof displacement and vulnerability indices, with irregular frames exhibiting significantly greater sensitivity. The study underscores the importance of occupancy control in seismically active regions.

Keywords: Elevation irregularity, Seismic performance, Overloading, Pushover analysis, Increased live load.

River Journal, 80–89.

1 Introduction

Earthquakes are inherently unpredictable and capable of causing severe structural damage. Failures during seismic events typically originate at weak points, often due to discontinuities in mass, stiffness, or geometry—features that define elevation irregularities [1,2]. These irregularities alter the dynamic behavior of buildings and increase their susceptibility to seismic damage. Structures are generally designed to resist dead, live, wind, and seismic loads. However, overloading—caused by unplanned storage, misplacement of construction materials, or overcrowding during events—can exceed design thresholds [3, 4]. Such excess loading increases stress on structural elements and the foundation, further exacerbating the risk of collapse [5]. Vertical irregularities, such as soft storeys, abrupt stiffness changes, or asymmetrical profiles, disrupt uniform force distribution during ground motion. Their presence, coupled with overloading, significantly elevates the seismic vulnerability of buildings and the associated risk to occupants. This study employs nonlinear static pushover analysis to assess the combined impact of elevation irregularity and increased live load on reinforced concrete frames. Regular and elevation-irregular configurations are analyzed under live loads varying from 5 kN/m^2 to 40 kN/m^2. Key parameters such as base shear, roof displacement, and vulnerability index are evaluated to highlight the heightened seismic risk caused by structural irregularity and overcrowding.

2 Pushover Analysis

Pushover analysis is a nonlinear static procedure used to estimate a structure's lateral load capacity under seismic excitation. The method involves modelling all load-resisting components—such as dead and live loads, and their force–deformation behavior—and applying incrementally increasing lateral forces to simulate ground motion [6, 7]. The resulting pushover curve represents base shear versus roof displacement, reflecting the structure's capacity to absorb and dissipate energy [8]. This approach is widely used to assess seismic performance, particularly for existing structures or performance-based design applications. The demand curve, derived from the response spectrum of the relevant seismic zone, soil type, and damping, is superimposed onto the capacity curve. Their intersection defines the performance point—an indicator of the expected structural response during an earthquake [9]. Figure 1 illustrates a typical pushover capacity curve and corresponding damage thresholds.

Damage is assessed across distinct states—slight, moderate, severe, or collapse-level—and separately for structural and non-structural components. The vulnerability index is computed by weighting the probability of each damage state (from fragility curves) with its associated cost fraction [9].

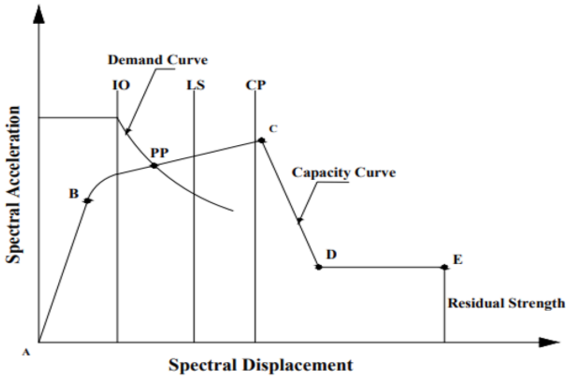

Figure 1 Capacity and demand curves showing damage state thresholds [9].

3 Characterization of the Structures

Structural irregularities arise from discontinuities in mass, stiffness, or geometry, which disrupt the uniform distribution of seismic forces and increase vulnerability. According to IS 1893:2016, vertical irregularities include abrupt changes in stiffness or mass over the height of a building, as illustrated in Figure 2 [2].

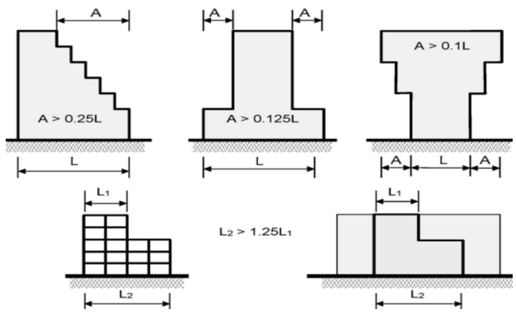

Figure 2 Elevation irregularities in structural configuration [2, 10].

This study analyzes three-storey reinforced concrete (RC) moment-resisting frames, both regular and elevation-irregular, using ETABS. Both configurations were modeled with identical material properties, story heights, bay widths, and cross-sectional dimensions. Special RC moment-resisting frames (SMRFs) were adopted as per IS 1893 and FEMA 440 guidelines [10, 11]. The geometric configuration and 3D views of both frames are illustrated in Figure 3. Table 1 presents the modeling parameters.

Table 1 Design details for frame configurations

Parameter	**Value**
Structure type	Special RC Moment Resisting Frame
Materials	M20 (Concrete), Fe415 (Steel)
Beam section	230 mm $\times$ 300 mm
Column section	300 mm $\times$ 300 mm
Slab thickness	150 mm
Storey height	3.0 m
Bay width	3.0 m
Plan size	9.0 m $\times$ 9.0 m
Seismic zone	Zone III
Soil type	Medium
Floor finish	1 kN/m^2
Live load	5–40 kN/m^2

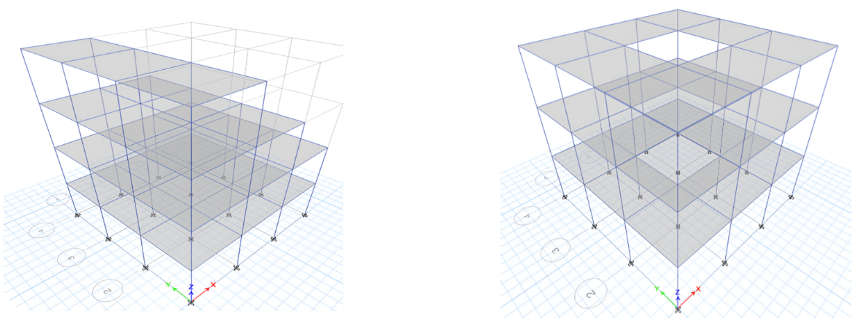

Figure 3 3D models of irregular (left) and regular (right) RC frames.

3.1 Structural Outline

The frames are designed for gravity loads as per IS 875, including slab self-weight (3.75 kN/m^2), wall loads (16.5 kN/m), finishes (1.0 kN/m^2), and live loads ranging from 5 to 40 kN/m^2 [10]. Pushover analysis is carried out using a displacement-based approach in accordance with FEMA 440 [11]. The seismic demand is defined using IS 1893 parameters with soil type II, an importance factor of 1.0, and a response reduction factor of 3.0.

3.2 Seismic Vulnerability Assessment

Seismic vulnerability refers to a structure's susceptibility to damage under a given intensity of shaking. It is commonly assessed using fragility functions that express the probability of exceeding specific damage states [12, 13]. These functions are critical for estimating potential risk and informing design or retrofitting strategies.

3.3 Vulnerability Index Calculation

The vulnerability index aggregates expected damage by combining the probability of exceeding a damage state with its cost fraction [4, 5]. Figure 4 outlines the damage probability matrix formulation.

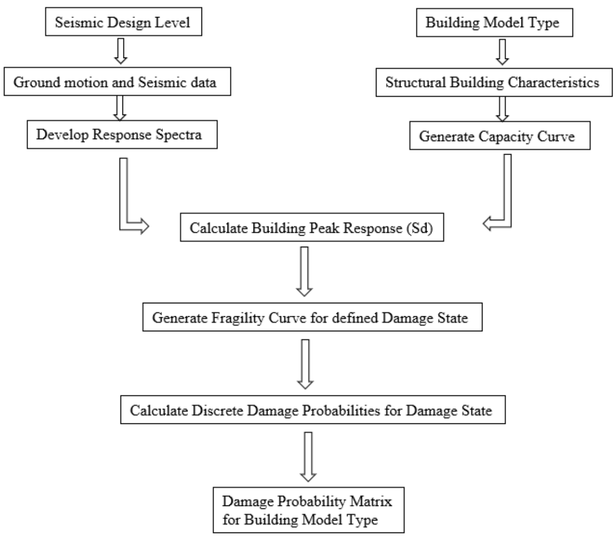

Figure 4 Flowchart for developing the damage probability matrix [14].

4 Results and Discussion

This section presents the seismic performance outcomes from nonlinear pushover analysis of regular and irregular RC frames subjected to increasing live loads. The response was evaluated based on four key metrics: base shear capacity, roof displacement, performance point shift, and vulnerability index. As shown in Figure 5, base shear increased with live load up to 35%, after which it declined. Regular frames exhibited higher lateral strength than irregular ones throughout the load range, highlighting the stabilizing effect of elevation uniformity. Figure 6 illustrates roof displacement behavior. Displacement increased with higher loads, and irregular frames showed nearly double the displacement of regular frames under the same conditions, indicating reduced lateral stiffness. Performance points, derived from the intersection of capacity and demand curves, are shown in Figure 7. As live load increased, the performance point shifted rightward—from elastic range toward collapse prevention—suggesting reduced ductility and increased vulnerability under overloading. The vulnerability index (Figure 8) rose steadily with live load increments from 5 kN/m^2 to 40 kN/m^2. Irregular frames consistently showed higher indices, reinforcing the compounded seismic risk due to elevation irregularity and overcrowding.

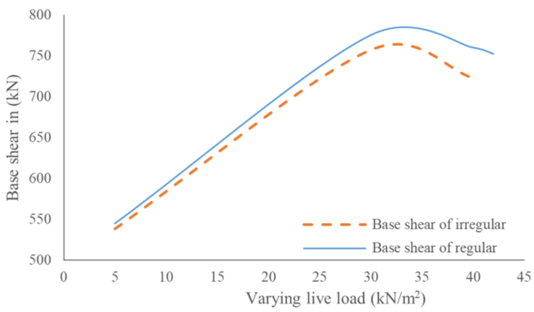

Figure 5 Base shear capacity of regular and irregular frames under increasing live loads.

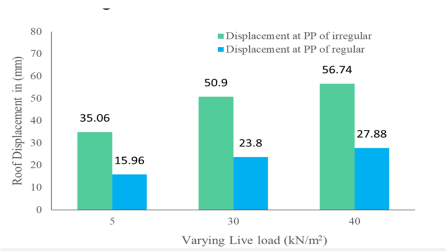

Figure 6 Roof displacement in regular and irregular frames for varying live loads.

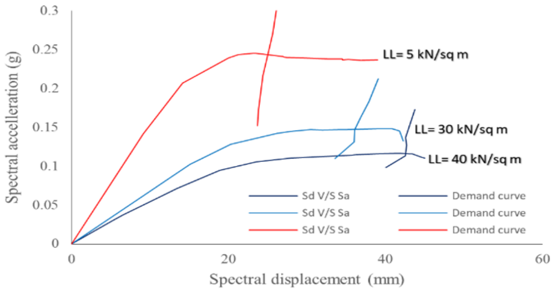

Figure 7 Pushover curves and performance points under different live loads.

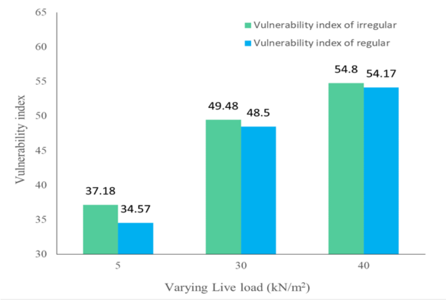

Figure 8 Vulnerability index of regular and irregular frames under varying live loads.

5 Conclusions

This study used nonlinear pushover analysis to evaluate the seismic behavior of reinforced concrete frames with regular and elevation-irregular configurations subjected to varying live loads. The results show that increased live loads significantly affect seismic performance by reducing overall stiffness and pushing the structure toward inelastic behavior. Base shear capacity increased up to a 35% rise in live load but declined beyond that point, indicating a loss of strength. Roof displacement and vulnerability indices rose steadily with live load, with irregular frames showing nearly twice the displacement and consistently higher vulnerability. The performance point shifted from elastic to near-collapse range under excessive loads, particularly in irregular frames. These findings confirm that elevation irregularities substantially increase seismic risk when combined with overloading due to overcrowding or mismanaged occupancy. Adherence to load design specifications and minimization of vertical irregularity are thus essential in buildings located in seismic zones.

References

[1] S. Prasad. Seismic performance study on RC wall buildings from pushover analysis. *IJRET: International Journal of Research in Engineering and Technology, pages 2321–7308, 2014.*

[2] Bureau of Indian Standards. IS 1893 (Part 1): Criteria for earthquake resistant design of structures – General provisions and buildings. New Delhi, 2016.

[3] C. Bedon, F. Stochino, and D. Honfi. Buildings and structures under extreme loads. *Applied Sciences, 10(16):5676, 2020.*

[4] S. Prasad and A. Krishnaiah. Effect of poor soil condition on seismic vulnerability of overcrowded building, 2022.

[5] R. F. Warner. Overload behavior of concrete structures: Design considerations. Australian Journal of Structural Engineering, 5(2):139–144, 2004.

[6] C. Bhatt and R. Bento. Comparison of nonlinear static methods for the seismic assessment of plan irregular frame buildings with non-seismic details. *Journal of Earthquake Engineering, 16(1):15–39, 2011.*

[7] S. Fotopoulou, S. Karafagka, C. Petridis, M. Manakou, E. Riga, and K. Pitilakis. Vulnerability assessment of school buildings: Generic versus building-specific fragility curves. Journal of Earthquake Engineering, pages 1–30, 2022.

[8] S. Antoniou and R. Pinho. Development and verification of a displacement-based adaptive pushover procedure. *Journal of Earthquake Engineering, 8(5):643–661, 2004.*

[9] Applied Technology Council. Seismic evaluation and retrofit of concrete buildings, ATC-40, vols. 1 and 2. Redwood City, CA, 1996.

[10] R. Peres, R. Bento, and J. M. Castro. Nonlinear static seismic performance assessment of plan-irregular steel structures. *Journal of Earthquake Engineering, 24(2):226–253, 2018.*

[11] Federal Emergency Management Agency. FEMA 440: Improvement of nonlinear static seismic analysis procedures. Washington, D.C., 2005.

[12] N. S. Roy and S. Choudhury. Seismic vulnerability assessment methods: A review. *Structural Integrity, pages 282–300, 2022.*

[13] D. Felsenstein, E. Elbaum, T. Levi, and R. Calvo. Post-processing HAZUS earthquake damage and loss assessments for individual buildings. Natural Hazards, 105(1):21–45, 2020.

[14] M. Biradar and S. Prasad. Influence of soil stiffness on seismic vulnerability of irregular buildings. Unpublished manuscript.

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A Comprehensive Review on the Emergence of Artificial Intelligence in Law

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Abstract

This paper presents a comprehensive review of the transformative influence of Artificial Intelligence (AI) within the legal domain. It examines AI's applications in legal research, case law analysis, contract automation, and predictive analytics, highlighting both opportunities and limitations. Machine learning and natural language processing technologies are redefining conventional legal practices, enhancing procedural efficiency and expanding access to justice. The review further explores the ethical dilemmas, implementation challenges, and evolving professional roles triggered by AI adoption. It underscores the need for interdisciplinary collaboration among legal professionals, technologists, and policymakers to formulate frameworks for the responsible integration of AI into the legal ecosystem.

Keywords: Implications of AI in legal practices, Applied AI, Generative AI, AI-generated legal documentation.

River Journal, 90–101.

1 Introduction

Artificial intelligence (AI) is increasingly redefining the legal domain, transforming legal research, documentation, contract management, and professional roles. As AI systems become integrated into law firms and judicial operations, traditional practices are evolving to incorporate automated reasoning, predictive analytics, and data-driven decision-making. This review focuses on three core dimensions of AI's integration into legal systems. First, AI enhances efficiency in legal research, case analysis, and contract automation, reshaping how legal professionals process information and prioritize tasks [1, 2]. Tools powered by natural language processing (NLP) and machine learning are accelerating document review and case outcome prediction, enabling practitioners to engage in higher-order legal reasoning. Second, the application of AI in legal contexts raises ethical concerns, including algorithmic bias, data privacy risks, and accountability gaps [3, 4]. These challenges necessitate robust ethical frameworks and regulatory safeguards to ensure that AI-based decisions uphold fairness, transparency, and justice. Third, the professional roles of lawyers and policymakers are undergoing redefinition. As AI takes on routine legal functions, practitioners are shifting toward interpretive, advisory, and supervisory responsibilities. Policymakers, meanwhile, must navigate a dynamic regulatory landscape to support technological innovation while preserving individual rights and institutional integrity [5,6].

To explore this evolving landscape, the review is guided by the following research questions:

- How is artificial intelligence transforming legal research, case analysis, and contract management?
- What ethical implications arise from the implementation of AI in legal practice, and how are these challenges being addressed?
- In what ways are AI technologies reshaping the roles and methodologies of lawyers and policymakers?

2 Methodology

This review adopts a structured literature analysis approach to examine the impact of Artificial Intelligence (AI) on the legal domain. Relevant literature was retrieved from scholarly databases including Scopus, Google Scholar, SSRN, IEEE Xplore, and the *Journal of Business Research*, focusing on publications from the past decade. A targeted keyword strategy was employed using terms such as "Artificial Intelligence in Law," "Legal Tech," and "AI and Legal Ethics." Boolean operators were applied to refine the search and improve relevance. This process initially yielded approximately 300 articles. Titles and abstracts were systematically screened to eliminate irrelevant or duplicate content, narrowing the pool to 40 core publications aligned with the review's research objectives. These sources were then critically analyzed to extract insights related to AI's applications in legal research, ethical challenges, and evolving legal roles. This method provided a solid foundation for synthesizing current knowledge, identifying trends, and contextualizing AI's transformative role in legal practice and policy development.

3 Literature Review

3.1 AI Applications and Evolving Roles in Legal Practice

The integration of Artificial Intelligence (AI) into legal practice has catalyzed a shift toward greater efficiency, precision, and strategic focus across multiple dimensions of legal work. A key area of transformation lies in legal research and case analysis, where AI tools—particularly those powered by natural language processing (NLP) and machine learning—enable rapid information retrieval, case outcome prediction, and contract analysis. These systems can scan large legal databases, identify relevant precedents, and assist in drafting tasks, allowing legal professionals to allocate more time to advisory and interpretive functions [1, 2]. Moreover, AI has implications for legal education and professional training. As automation increasingly handles routine legal tasks, the role of lawyers is evolving from technical execution to strategic oversight. This shift necessitates the development of new competencies, such as data interpretation, digital ethics, and AI tool proficiency, which legal education programs are beginning to integrate into their curricula [5, 6]. Simultaneously, AI introduces ethical complexities, particularly around algorithmic transparency, bias, and data privacy. These concerns underscore the need for interdisciplinary frameworks that embed accountability and fairness into legal AI systems [3, 4].

Scholars argue that without proactive governance and ethical design, AI risks reinforcing existing inequalities or eroding trust in the justice system. Overall, the literature highlights AI as both a disruptive force and a transformative tool, offering opportunities to enhance legal operations while prompting a reevaluation of foundational professional roles and ethical standards within the legal sector.

3.2 AI's Practical Impact, Ethical Ramifications, and Future Trajectories in Law

Artificial Intelligence (AI) is reshaping core functions in the legal domain, from streamlining legal research to transforming contract management and decision-making processes. AI-driven systems can rapidly analyze complex legal documents, assess risk, and generate predictive insights regarding case outcomes [7, 11]. Tools such as ROSS Intelligence and Kira Systems exemplify this shift by enabling automated legal research and contract review, significantly reducing turnaround times while improving accuracy [16, 17]. A range of AI applications influencing various legal processes is summarized in Table 1. These studies highlight how AI technologies have advanced efficiency in legal analysis, strategic decision-making, contract automation, and risk prediction across different legal and adjacent sectors.

However, the integration of AI raises considerable ethical concerns. Algorithmic bias, data security, and lack of transparency in decision-making remain central issues. If not addressed, these risks can perpetuate systemic inequalities or undermine trust in the legal system [18,26]. Regulatory frameworks like the General Data Protection Regulation (GDPR) offer foundational guidance, yet their adaptation to dynamic AI systems remains a work in progress [30]. This evolution necessitates upskilling through interdisciplinary legal education, integrating knowledge of AI systems, ethics, and governance. A summarized overview of ethical and professional dimensions impacted by AI adoption is provided in Table 2. As AI continues to influence legal practice, a collaborative approach involving technologists, legal experts, and ethicists is essential. Ensuring that AI enhances, rather than compromises, the legal profession will depend on thoughtful implementation, clear accountability, and ongoing adaptation.

Table 1 AI applications transforming legal research, case analysis, and contract management

No.	Title of Paper	Literature Highlights
1	Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects	Emphasizes AI's use in document analysis, contract automation, and legal efficiency [7]
2	Understanding the interplay of artificial intelligence and strategic management: four decades of research in review	Explores AI-based legal case prioritization and strategic decision-making [8]
3	Intelligent purchasing: How artificial intelligence can redefine the purchasing function	Highlights AI's role in predictive analytics for contract negotiation [9]
4	Artificial intelligence techniques for photovoltaic applications: A review	Demonstrates AI's adaptability to complex data analysis, with parallels to legal analytics [10]
5	Machine learning and AI in marketing – Connecting computing power to human insights	Applies predictive modeling for case outcome forecasting in law [11]
6	Artificial Intelligence for Mental Health and Mental Illnesses: an Overview	Supports applications in forensic psychology and courtroom competency assessments [12]
7	Machine learning in cardiovascular medicine: are we there yet?	Indicates AI's potential use in malpractice litigation and case evaluations [13]
8	Machine learning in agriculture: A comprehensive updated review	Suggests AI's use in precedent classification and legal document management [14]
9	Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis	Illustrates AI's capacity for legal compliance and financial regulation analysis [15]
10	How artificial intelligence will affect the practice of law	ROSS Intelligence improves legal research and court outcome predictions [16]

3.3 The Balance: Limits and Risks of AI in Law

While Artificial Intelligence (AI) presents significant advancements in legal efficiency and decision-making, its limitations must not be overlooked. AI systems lack contextual sensitivity, emotional reasoning, and interpretive nuance—qualities essential to legal judgment. Furthermore, reliance on historical datasets introduces the risk of perpetuating bias, particularly in predictive policing and risk scoring [37]. Another central concern is privacy. Legal datasets often contain sensitive personal information, and improper use or inadequate protection may compromise client confidentiality. These risks underscore the need for stringent data governance and compliance with evolving privacy frameworks [38]. Transparency and explainability are vital to ensure trust in AI-generated legal outcomes.

Table 2 Summary of ethical and professional impacts of AI in legal practice

Theme	**Impact on Legal Practice and Policy**
AI for Legal Education and Training	Personalized learning systems and simulation-based tools are transforming legal education; law schools must revise curricula to incorporate AI and technology [34]
AI and Privacy Law Compliance	AI systems assist with managing GDPR and other data laws, automating privacy assessments and compliance workflows [13, 35]
AI in Environmental Law and Policy	AI is applied in monitoring compliance, forecasting environmental impacts, and supporting policy design and regulation [35]
AI in Legal Analytics	Legal professionals are using AI for trend analysis, litigation forecasting, and strategy planning based on large legal datasets [36]
AI for Contract Analysis and Management	Automated review and drafting tools are streamlining contract workflows, prompting a shift in legal roles toward negotiation and strategic oversight [17]
AI in Predictive Policing and Criminal Justice	Tools are being trialed to assess risk levels and suggest actions pre-trial; this raises fairness and accountability concerns [20]
Ethical and Regulatory Frameworks for AI	The legal profession must shape adaptive regulatory structures to govern AI ethically, protecting individual rights and legal integrity [11, 30]

The complexity of AI also challenges traditional legal doctrines of liability. When decisions are made by opaque algorithms, assigning responsibility becomes difficult—raising concerns for malpractice, ethical standards, and due process [39]. A summary of these concerns and recommended mitigation measures is presented in Table 3. Therefore, while AI can optimize and augment legal practice, it cannot substitute for human judgment. Legal systems must adopt a balanced approach—leveraging AI's capabilities while enforcing ethical safeguards, fairness metrics, and accountability mechanisms. Sustained interdisciplinary collaboration is essential to ensure that AI supports, rather than disrupts, core principles of justice.

Table 3 Key ethical concerns and corresponding mitigation strategies in AI for legal systems

Ethical Concern	Recommended Mitigation Strategy
Accountability	Ensure transparency and traceability through explainable AI systems and audit trails
Privacy	Implement strong data protection laws, anonymization protocols, and informed consent frameworks
Bias	Use fairness-aware algorithms, diversify training data, and conduct regular bias audits

4 Results and Discussion

The integration of Artificial Intelligence (AI) into legal practice has led to substantial operational improvements, particularly in automating repetitive tasks, streamlining legal research, and enhancing predictive analytics. Tools like ROSS Intelligence and Kira Systems have demonstrated tangible benefits in contract management, document review, and legal reasoning, allowing professionals to devote more time to strategic analysis and client-focused problem-solving [16, 17]. Despite these advantages, the findings highlight that Despite these benefits, AI systems can misinterpret data or produce outcomes lacking legal nuance. Concerns related to ethical governance, particularly data privacy, algorithmic bias, and explainability, remain central to ongoing discourse. The deployment of AI without adequate regulatory frameworks can inadvertently undermine legal integrity and public trust [30, 39].

A key insight from the literature is the dual nature of AI's influence: while it enhances efficiency and accessibility, it also necessitates significant adaptation in legal education and professional development. Legal practitioners must cultivate new competencies in AI literacy, digital ethics, and regulatory interpretation to remain effective in this evolving landscape. Similarly, policymakers are being called upon to design legal frameworks that both encourage innovation and enforce accountability. Importantly, AI holds promise for democratizing legal services by improving access to justice. With automation reducing time and cost, AI-based legal assistants and chatbots could offer preliminary support to underserved populations. However, to ensure equity, these technologies must be designed with transparency, fairness, and inclusivity in mind. Ultimately, the successful adoption of AI in the legal field will depend on collaborative efforts among legal professionals, technologists, and regulators.

A balanced approach—emphasizing both technical efficiency and ethical safeguards—will be essential for leveraging AI's capabilities without compromising foundational legal principles such as due process, impartiality, and justice.

5 Conclusion

The integration of Artificial Intelligence (AI) into legal practice is driving a fundamental transformation in how legal professionals conduct research, manage documentation, and deliver services. AI tools are enhancing the speed, accuracy, and efficiency of legal processes, empowering professionals to focus on higher-order tasks such as strategy, negotiation, and policy interpretation. Technologies such as ROSS Intelligence and Kira Systems exemplify the automation of traditionally manual tasks, demonstrating AI's capacity to augment legal workflows. However, this transformation is not without its challenges. The deployment of AI raises significant ethical and operational concerns, especially in relation to algorithmic fairness, data privacy, and accountability. Without robust governance frameworks, such issues could compromise the integrity of legal systems and erode public trust. Additionally, the complexity and opacity of AI models can obscure responsibility for errors or biased outcomes, complicating their use in sensitive legal contexts. This review also acknowledges several limitations. Given the rapid pace of AI development, this study may not fully capture the breadth of emerging applications or ethical dilemmas. Moreover, the interpretability of AI systems and their long-term impact on legal education and professional practice remain open areas for future research. To support responsible AI adoption, legal professionals and policymakers must prioritize interdisciplinary collaboration, adherence to ethical standards, and continuous upskilling. Law curricula should incorporate AI literacy and digital governance, while regulatory bodies must define adaptive policies to guide AI integration. In conclusion, AI offers transformative potential for the legal domain. Yet, realizing these benefits requires a careful balance between technological innovation and ethical oversight. With thoughtful integration, AI can expand access to justice, streamline legal workflows, and uphold the foundational values of the legal profession.

References

[1] Sulea, O. M., Zampieri, M., Vela, M., & van Genabith, J. (2017). Predicting the law area and decisions of French Supreme Court cases. *Proceedings of the International Conference on Law, Language and Data Processing*, 1–10.

[2] Surden, H. (2014). Machine learning and law. *Washington Law Review*, *89*(1), 87–115.

[3] Lehr, D., & Ohm, P. (2017). Playing with the data: What legal scholars should learn about machine learning. *Emory Law Journal*, *51*(1), 87–148.

[4] Calo, R. (2017). Artificial intelligence policy: A primer and roadmap. *University of California Davis Law Review*, *51*(2), 399–435.

[5] Remus, D., & Levy, F. (2016). Can robots be lawyers? Computers, lawyers, and the practice of law. *SSRN Electronic Journal*.

[6] Casey, A. J., & Niblett, A. (2016). Self-driving laws. *University of Toronto Law Journal*, *66*(4), 429–461.

[7] Mikalef, P., Krogstie, J., Pappas, I. O., & Giannakos, M. (2018). Investigating the effects of big data analytics capabilities on firm performance: The mediating role of dynamic capabilities. *Information & Management*, *55*(8), 103–118.

[8] Popovič, A., Hackney, R., & Coelho, P. S. (2012). Towards business intelligence systems success: Effects of maturity and culture on analytical decision making. *Decision Support Systems*, *54*(1), 729–739.

[9] Baryannis, G., Dani, S., & Antoniou, G. (2019). Predictive analytics and artificial intelligence in supply chain management: Review and implications for the future. *Computers & Industrial Engineering*, *137*, 106024.

[10] Yadav, A. K., & Chandel, S. S. (2014). Artificial intelligence techniques for solar photovoltaic applications: A review. *Renewable and Sustainable Energy Reviews*, *32*, 486–498.

[11] Davenport, T. H., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*, 24–42.

[12] Ng, M. Y., Aggarwal, N. K., Hosanagar, K., & Kohli, R. (2020). Artificial intelligence for mental health and mental illnesses: An overview. *Current Psychiatry Reports*, *22*, 84.

[13] Johnson, K. W., Torres Soto, J., Glicksberg, B. S., Shameer, K., Miotto, R., Ali, M., ... & Dudley, J. T. (2018). Artificial intelligence in cardiology. *Journal of the American College of Cardiology*, *71*(23), 2668–2679.

[14] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, *147*, 70–90.

[15] Malo, P., Sinha, A., Takala, P., Korhonen, P., & Wallenius, J. (2019). Artificial intelligence in finance: Promises and challenges. *Journal of Financial Regulation and Compliance*, *27*(1), 3–20.

[16] McGinnis, J. O., & Pearce, R. G. (2014). The great disruption: How machine intelligence will transform the role of lawyers in the delivery of legal services. *Fordham Law Review*, *82*(6), 3041–3066.

[17] Ashley, K. D. (2017). *Artificial intelligence and legal analytics: New tools for law practice in the digital age*. Cambridge University Press.

[18] Sartor, G. (2020). Artificial intelligence and legal responsibility. *Philosophy & Technology*, *33*, 271–291.

[19] Greenhalgh, T., Shaw, S., Wherton, J., Vijayaraghavan, S., & Stones, R. (2019). Management of medico-legal risks in digital health era: A scoping review. *Journal of Medical Internet Research*, *21*(1), e112.
[20] Pagallo, U. (2017). The impact of artificial intelligence on criminal law and its ethical implications. *Philosophy & Technology*, *30*(4), 441–456.
[21] Vollmer, S., Mateen, B. A., & Boztas, A. (2020). Recommendations for the ethical design and implementation of artificial intelligent care providers. *The Lancet Digital Health*, *2*(6), e277–e289.
[22] Lenz, R., & Kuhn, K. A. (2004). Decision support and ethics in artificial intelligence-based accounting systems. *Artificial Intelligence in Accounting and Auditing*, *8*, 37–51.
[23] Salles, A., Evers, K., & Farisco, M. (2020). Your robot therapist will see you now: Ethical implications of embodied artificial intelligence in psychotherapy. *Frontiers in Psychology*, *11*, 793.
[24] Mills, J., Trevino, K., Ensor, B., Youngwerth, J., & Fisch, M. (2021). Ethical challenges of AI in palliative care: A narrative review. *BMC Palliative Care*, *20*(1), 15.
[25] McQuillan, D. (2018). AI and ethics: A narrative review. *Big Data & Society*, *5*(1), 1–12.
[26] Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, *1*, 389–399.
[27] Binns, R. (2018). Fairness in machine learning: Lessons from political philosophy. *Proceedings of the 2018 Conference on Fairness, Accountability and Transparency*, 149–159.
[28] Yu, H., Shen, Z., & Miao, C. (2019). Artificial intelligence ethics in environmental protection. *AI & Society*, *34*(2), 219–227.
[29] Hosanagar, K., & Jair, V. (2018). We need transparency in algorithms, but too much can backfire. *Harvard Business Review*.
[30] Wachter, S., Mittelstadt, B., & Floridi, L. (2017). Why a right to explanation of automated decision-making does not exist in the general data protection regulation. *International Data Privacy Law*, *7*(2), 76–99.
[31] Calo, R., & Kerr, I. (2013). Robotics and the lessons of cyberlaw. *California Law Review*, *103*(3), 513–563.
[32] IEEE Global Initiative. (2019). *Ethically aligned design: A vision for prioritizing human well-being with autonomous and intelligent systems*. IEEE Standards Association.
[33] Kira Systems. (2020). *Kira use cases and law firm applications*. White Paper.
[34] Cano, A. R., & Garcia-Sanchez, R. (2020). Artificial intelligence in legal education. *Education and Information Technologies*, *25*(5), 4355–4372.
[35] Voigt, P., & Von dem Bussche, A. (2017). *The EU General Data Protection Regulation (GDPR)*. Springer.
[36] Aletras, N., Tsarapatsanis, D., Preoţiuc-Pietro, D., & Lampos, V. (2016). Predicting judicial decisions of the European Court of Human Rights: A natural language processing perspective. *PeerJ Computer Science*, *2*, e93.
[37] Barocas, S., & Selbst, A. D. (2016). Big data's disparate impact. *California Law Review*, *104*(3), 671–732.
[38] Floridi, L., & Cowls, J. (2019). A unified framework of five principles for AI in society. *Harvard Data Science Review*, *1*(1).

[39] Casey, B., Farhangi, A., & Vogl, R. (2019). Rethinking explainable machines: The GDPR's right to explanation debate and the rise of algorithmic audits in enterprise. *Berkeley Technology Law Journal*, *34*(1), 143–188.

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