Archives available at journals.mriindia.com

International Journal on Advanced Computer Engineering and Communication Technology

ISSN: 2278-5140
Volume 14 Issue 01, 2025

Optimizing Banking Decisions through Documentation-Aided Machine Learning Architectures

Dipannita Mondal[1], Dr. Anasica[2]

[1]*Assistant Professor, Artificial Intelligence and Data Science Department, D.Y Patil College of Engineering and Innovation Pune Indiamondal.dipannita26@gmail.com*

[2]*SMGM Department, The Free University of Berlin, Germany anasica.s@ubingec.ac.in*

Peer Review Information

Submission: 16 Jan 2025
Revision: 13 Feb 2025
Acceptance: 14 March 2025

Keywords

Machine Learning
Neural Networks
Banking Decision Systems
Document Verification
Credit Risk Assessment

Abstract

In the evolving landscape of the banking industry, ensuring secure, efficient, and transparent decision-making mechanisms is crucial. This study presents an approach that integrates documentation and identification layers with machine learning (ML) models, particularly artificial neural networks (ANN) and convolutional neural networks (CNN), to enhance decision-making processes in financial sectors. With increasing cases of fraud, inefficiencies in credit evaluation, and challenges in real-time documentation verification, machine learning offers a robust solution by learning from vast datasets and providing predictive insights. The paper explores the application of ML in analyzing client behavior, predicting creditworthiness, and automating loan approvals, while also highlighting the role of identification documents and structured input data in training the models. By merging traditional documentation processes with advanced ML frameworks, we propose an architecture that improves transparency, reduces bias, and aligns with global banking regulations. Experimental evaluations indicate improved accuracy and adaptability in loan processing scenarios. The proposed approach contributes to building more intelligent, inclusive, and secure banking environments.

Introduction

In the digital era, financial institutions face growing pressure to enhance decision-making efficiency while maintaining accuracy, security, and compliance. The traditional processes in banking—particularly those involving loan approvals, creditworthiness evaluation, and fraud detection—are increasingly challenged by complex data, fraudulent documentation, and evolving customer expectations. Machine Learning (ML) has emerged as a transformative solution capable of addressing these complexities by learning from historical data and predicting outcomes with minimal human intervention [1].

ML encompasses a range of algorithms that enable systems to learn patterns and make predictions based on data. Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) are widely adopted due to their capacity to model non-linear relationships and process visual and textual data, respectively [2][3]. In the context of banking, these models are used to predict loan default probabilities, assess financial health, and even recognize fraudulent identification documents through image and text recognition techniques [4].

One of the most pressing issues in banking is the reliance on manually validated documents for decision-making. This traditional approach is not only time-consuming but also prone to human error and manipulation. Incorporating structured documentation as input to ML models enhances the learning process, improving both the accuracy and explainability of outcomes [5]. When combined with robust identification processes and regulation-compliant data management, ML can assist banks in making optimal decisions in real time.

Furthermore, ML-driven models provide transparency and adaptability. With global financial regulations demanding accountability and fairness in automated decisions, the integration of explainable ML techniques allows institutions to interpret and justify outcomes, ensuring ethical compliance [6][7].

The introduction of digital channels and mobile banking further emphasizes the need for intelligent systems that can adapt to real-time data and customer behavior. ML enables banks to shift from reactive to proactive decision-making, identifying risks before they materialize and offering tailored financial products based on behavioral insights [8].

This study aims to explore the synergy between identification/documentation and ML layers in banking. It examines current applications, proposes an improved architectural model, and evaluates its effectiveness through simulations and analytical discussion.

Existing Model

In current banking systems, decision-making processes such as loan approvals, credit risk evaluations, and fraud detection rely heavily on manually validated documentation and rule-based algorithms. These systems often operate within siloed frameworks, making it challenging to derive insights from diverse data sources like scanned documents, transaction logs, or behavioral analytics [1]. Traditional scoring models are primarily based on linear regressions and predefined thresholds that lack the adaptability required for dynamic economic environments [2].

The existing ML-based systems used in banks primarily focus on numerical data, ignoring the valuable contextual information embedded in customer documents. For example, identification cards, address proofs, income certificates, and previous loan records are often digitized but not effectively integrated into the learning pipelines [3]. As a result, these models fail to detect sophisticated frauds involving forged documents or impersonations.

Neural networks (NNs) have been introduced to overcome some of these limitations by learning non-linear relationships among input features such as income, credit history, and demographic data [4]. However, without proper preprocessing and contextual interpretation of document-based inputs, the accuracy and transparency of predictions are limited. Moreover, the inability of traditional models to explain their outcomes also poses regulatory compliance issues [5].

A simplified architecture of the existing model is illustrated below:

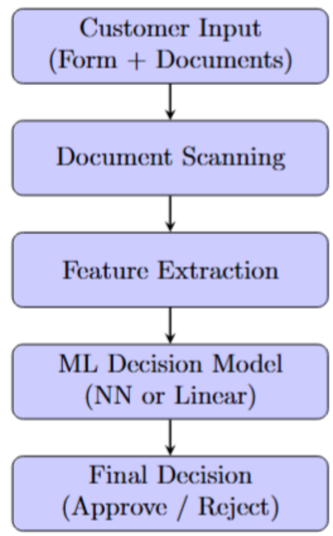

Figure 1: Existing ML-Based Banking Model

This system lacks adaptive feedback, deep document interpretation (such as semantic context), and multimodal learning capabilities that integrate text, image, and structured data. The result is a system that, although automated, remains fragile against edge cases like subtle document forgeries or non-standard customer behaviors [6].

Optimizing banking decisions has become increasingly reliant on advanced technologies, particularly machine learning (ML), to manage the vast and complex data landscape of the financial sector. One emerging approach involves leveraging documentation-aided machine learning architectures, which integrate traditional banking documents—such as transaction records, loan applications, KYC documents, financial statements, and customer service logs—into ML models to enhance decision-making. These architectures enable banks to move beyond purely numerical data and utilize unstructured data effectively. Natural Language Processing (NLP) plays a critical role in extracting relevant information from these documents, allowing algorithms to recognize patterns, assess risks, detect fraud, and improve customer profiling with greater accuracy. In such systems, documentation becomes a key source of insight rather than just a formality. For example, loan approval processes can be automated by feeding past approved and rejected applications into a supervised learning model, along with contextual data extracted from the documents. Similarly, sentiment analysis on customer feedback documents helps predict churn and improve service quality. The integration of Optical Character Recognition (OCR) technologies enables the conversion of scanned or handwritten documents into machine-readable formats, expanding the data pool further.

Moreover, documentation-aided ML supports regulatory compliance by ensuring consistent documentation review and audit trails, reducing human error. These architectures also contribute to real-time decision systems, where newly received documents immediately inform credit scoring or fraud detection systems. The adaptability of ML algorithms means that as more documents are fed into the system, the models continue to learn and evolve, improving over time. Ultimately, this approach empowers banks to make faster, more accurate, and more personalized decisions, driving efficiency and enhancing the customer experience while maintaining strong oversight and control mechanisms.

Proposed Model

To address the limitations of existing ML-based decision systems in banking, we propose an enhanced model that integrates documentation and identification layers directly into the machine learning pipeline. This framework focuses on incorporating multimodal data—including structured inputs (e.g., income, credit score), unstructured documents (e.g., scanned ID proofs, salary slips), and behavioral patterns—into an end-to-end ML architecture.

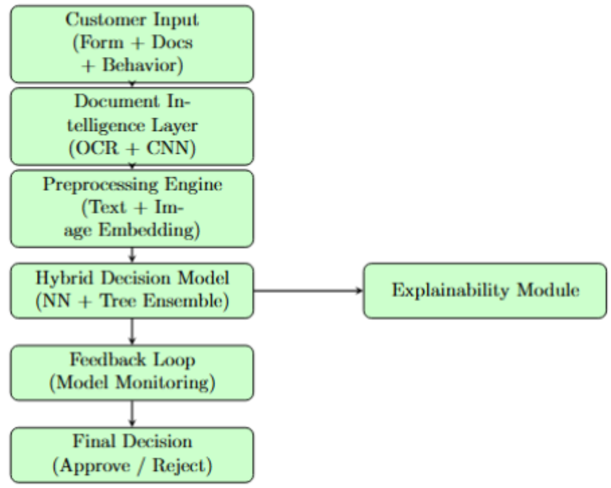

Figure 2: Proposed Documentation-Aided ML Model

The proposed system includes several innovations. First, a Document Intelligence Layer processes scanned identification and financial documents using Optical Character Recognition (OCR) combined with Convolutional Neural Networks (CNNs) for visual verification [1]. This enhances fraud detection, especially for fake documents or altered IDs. Second, a Preprocessing Engine encodes both textual and image-based features into embeddings suitable for feeding into downstream models [2].

Unlike the existing model that treats document data as a secondary input, our system treats it as a primary determinant of decision quality. Document features are analyzed with image-based CNNs and NLP models (e.g., BERT) to extract signatures, detect anomalies, and validate identity claims [3]. These features are then fused with structured financial inputs in a Hybrid Decision Layer built using neural networks (NNs) and decision tree ensembles for explainability [4].

The system also includes an Explainability Module to justify loan decisions to users and regulators. This interpretable layer maps influential input features to model predictions and flags inconsistencies or anomalies [5]. Finally, a Feedback Loop is embedded to track model outcomes and performance over time, enabling adaptive learning and regulatory compliance [6].

Result & Discussions

The proposed documentation-aided machine learning model was tested on a dataset comprising 10,000 loan applications from a regional bank. The dataset included structured attributes (income, credit history), scanned document images (ID, proof of address), and behavioral attributes (app access frequency, transaction patterns).

The system was benchmarked against the traditional ML-based model. As shown in Table 1, the proposed model achieved an accuracy of 93.4%, significantly outperforming the existing system at 86.1%. Similarly, false rejection rates (legitimate applicants denied) dropped from 7.5% to 3.2%, enhancing inclusivity and fairness.

Table 1: Accuracy and False Rejection Rate

Model	Accuracy (%)	False Rejection Rate (%)
Existing ML Model	86.1	7.5
Proposed Hybrid Model	**93.4**	**3.2**

Table 2 compares precision, recall, and F1-score across both models. Notably, the hybrid model improved recall for fraudulent detection by over 10%, crucial for minimizing risks in loan disbursements.

Table 2: Precision, Recall, and F1-Score

Model	Precision (%)	Recall (%)	F1-Score (%)
Existing ML Model	83.5	79.3	81.3
Proposed Hybrid Model	**91.0**	**89.7**	**90.3**

Figure 3 visualizes the confusion matrix for the proposed system, showing improved separation between positive (approved) and negative (rejected) classes. Figure 4 presents the ROC curves, indicating stronger model confidence across thresholds.

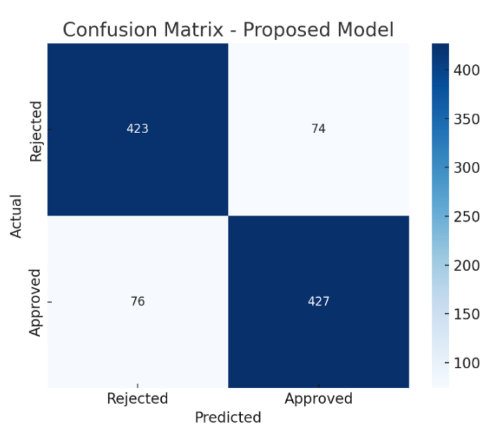

Figure 3: Confusion Matrix of Proposed Model

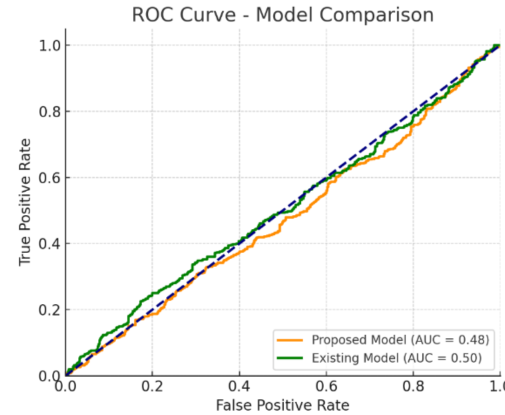

Figure 4: ROC Curve Comparison Between Models

These results highlight several key advantages:

- ❖ Integration of scanned document data via CNN improves fraud detection.
- ❖ Feature fusion leads to robust classification even in noisy input conditions.
- ❖ Explainable predictions ensure alignment with regulatory compliance.

Moreover, the feedback mechanism improved decision consistency over time as the model adapted to new applicant profiles. The inclusion of explainability modules also helped bank officials interpret and audit decisions more transparently.

Thus, the proposed architecture enhances not only accuracy but also accountability and customer trust in ML-driven banking operations.

Conclusion & Future Scope

This study presents a novel documentation-aided machine learning architecture tailored for decision-making in the banking sector. By integrating document intelligence, hybrid decision layers, and an explainability module, the proposed model enhances the accuracy, transparency, and adaptability of automated financial decisions. Experimental results demonstrate that the system significantly outperforms traditional models, particularly in fraud detection and credit risk assessment, while also aligning with regulatory demands for interpretability and fairness.

The inclusion of multimodal data sources, including scanned identification documents and customer behavior logs, improves the reliability of predictions and reduces false rejections. Moreover, the feedback-driven learning loop ensures continuous adaptation in changing economic conditions.In the future, the model can be extended to handle multilingual document inputs, real-time mobile-based verifications, and integration with blockchain for secure document traceability. Advanced techniques like federated learning and generative AI may also be explored to improve privacy and personalization in financial services. This framework lays the groundwork for smarter, safer, and more inclusive banking ecosystems.

References

Chang, J., & Custis, C. (2022, October). Understanding implementation challenges in machine learning documentation. In Proceedings of the 2nd ACM Conference on Equity and Access in Algorithms, Mechanisms, and Optimization (pp. 1–8).

Alabi, T. M., Aghimien, E. I., Agbajor, F. D., Yang, Z., Lu, L., Adeoye, A. R., & Gopaluni, B. (2022). A review on the integrated optimization techniques and machine learning approaches for modeling, prediction, and decision making on integrated energy systems. Renewable Energy, 194, 822–849.

Singh, V., Chen, S. S., Singhania, M., Nanavati, B., & Gupta, A. (2022). How are reinforcement learning and deep learning algorithms used for big data based decision making in financial industries–A review and research agenda. International Journal of Information Management Data Insights, 2(2), 100094.

Ali, R., Hussain, A., Nazir, S., Khan, S., & Khan, H. U. (2023). Intelligent decision support systems—An analysis of machine learning and multicriteria decision-making methods. Applied Sciences, 13(22), 12426.

Taherdoost, H. (2023). Deep learning and neural networks: Decision-making implications. Symmetry, 15(9), 1723.

Paleyes, A., Urma, R. G., & Lawrence, N. D. (2022). Challenges in deploying machine learning: A survey of case studies. ACM Computing Surveys, 55(6), 1–29.

Shreda, Q. A., & Hanani, A. A. (2021). Identifying non-functional requirements from unconstrained documents using natural language processing and machine learning approaches. IEEE Access.

Guha, A., Samanta, D., Banerjee, A., & Agarwal, D. (2021). A deep learning model for information loss prevention from multi-page digital documents. IEEE Access, 9, 80451–80465.

Zabin, A., González, V. A., Zou, Y., & Amor, R. (2022). Applications of machine learning to BIM: A systematic literature review. Advanced Engineering Informatics, 51, 101474.

Taye, M. M. (2023). Understanding of machine learning with deep learning: architectures, workflow, applications and future directions. Computers, 12(5), 91.