iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** VIII **Month of publication:** August 2026

DOI: https://doi.org/10.22214/ijraset.2026.84675

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VIII Aug 2026- Available at www.ijraset.com

A Machine Learning-Based UPI Security and Fraud Detection

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Abstract: ***Unified Payments Interface (UPI) has revolutionized digital payments in India, enabling seamless, real-time money transfers between accounts. However, its growing popularity has made it increasingly susceptible to fraudulent activities such as phishing, account takeovers, and transaction manipulation. This study introduces a hybrid fraud detection system integrating Convolutional Neural Networks (CNN) with Autoencoder, Local Outlier Factor (LOF), and K-Means Clustering to detect anomalous UPI transactions efficiently. The system utilizes anonymized UPI transaction data including transaction amount, time, device identifiers, and geolocation. Preprocessing involved encoding categorical features, normalizing numerical variables, and addressing missing data. The proposed hybrid approach was evaluated using accuracy, precision, recall, F1-score, and AUC-ROC metrics, achieving higher accuracy and fewer false positives compared to traditional methods. The findings highlight that deep learning combined with unsupervised techniques offers a robust solution for ensuring secure and reliable UPI payment operations.***

Index Terms: ***UPI fraud detection, convolutional neural networks, Autoencoder, Local Outlier Factor, K-Means Clustering, machine learning, anomaly detection, financial security.***

I. INTRODUCTION

The Unified Payments Interface (UPI) has emerged as one of India's most transformative digital payment platforms. It allows instant peer-to-peer fund transfers using mobile applications, fostering financial inclusion and convenience. However, the rapid adoption of UPI has also attracted cybercriminals, leading to increased fraudulent transactions, phishing attacks, and unauthorized access to user accounts. Traditional rule-based fraud detection systems often fail to adapt to dynamic and evolving fraud patterns. They rely on static thresholds, which may result in either missed detections or high false-positive rates. Consequently, there is a growing need for intelligent, real-time fraud detection systems capable of learning from transaction behavior and identifying suspicious activities with high precision.

Machine Learning (ML) and Deep Learning (DL) techniques offer advanced capabilities for identifying hidden relationships and detecting anomalies in complex financial datasets. In this research, we develop a hybrid deep learning framework based on Convolutional Neural Networks (CNN), Autoencoder, Local Outlier Factor (LOF), and K-Means Clustering. This framework enhances fraud detection accuracy, reduces false alarms, and ensures faster response times for digital payment security.

The remainder of this paper is structured as follows: Section II presents a literature survey, Section III outlines the methodology, Section IV explains the mathematical background, Section V discusses results, and Section VI concludes the work.

II. LITERATURE SURVEY

Maes et al. [1] developed a fraud detection system using Bayesian networks and neural networks to identify credit card anomalies. Their approach analyzed customer spending patterns and transactional attributes, achieving a strong accuracy rate on large datasets. However, the model required frequent retraining as fraudulent strategies evolved, making it computationally expensive for real-time systems.

Bentley et al. [2] introduced a Fuzzy-ID3 algorithm to classify financial transactions as legitimate, suspicious, or fraudulent using fuzzy logic integrated with decision trees. The system improved interpretability and reduced false positives but was limited by static rule sets that failed to adapt to changing fraud patterns over time.

Kundu et al. [3] proposed a hybrid sequence alignment approach combining anomaly and misuse detection for identifying financial frauds. Their system compared new transactions with historical user behavior using the BLAST–SSAHA technique, leading to high accuracy in identifying fraud. However, the algorithm's computational cost restricted scalability in real-time applications.

Rani et al. [4] designed a machine learning-based "Secure UPI" framework utilizing the XGBoost algorithm to analyze attributes such as transaction frequency, amount, and geolocation. The model achieved an accuracy of 98.2% and offered instant alerts for abnormal transactions. Despite its success, the system required periodic retraining and large datasets for sustained accuracy.

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Patil et al. [5] presented a hybrid framework that combined supervised learning and unsupervised anomaly detection to identify UPI fraud. Their approach employed behavioral analytics and pattern recognition to improve detection rates. The model achieved better precision than traditional rule-based systems but faced challenges in balancing recall and accuracy for minority fraud classes.

Lakshmi and Deepa [6] evaluated the security architecture of UPI mobile applications and identified vulnerabilities in authentication, encryption, and transaction verification. They recommended AI-driven fraud prevention, user education, and behavioral tracking to enhance digital transaction safety. However, they noted that implementing such systems required compliance with strict financial regulations.

Kolekar et al. [7] analyzed preventive technologies for digital banking security, emphasizing encryption, blockchain, and biometrics. Their work concluded that a combination of cryptographic measures and ML-based fraud detection offers the best protection against unauthorized access. Nevertheless, system cost and complexity remained key limitations.

Patil and Sharma [8] proposed a hybrid approach combining clustering and ensemble methods to improve the scalability of fraud detection systems. Their model achieved high accuracy on large datasets while minimizing false positives. However, the authors reported interpretability issues that could hinder its adoption in regulated financial systems.

Boulieris et al. [9] utilized natural language processing (NLP) to detect fraudulent intent by analyzing textual data such as transaction descriptions and complaint logs. Their model improved classification performance by identifying semantic cues in customer interactions. Although effective, it raised privacy and data governance concerns when applied to sensitive banking information.

Adekunle et al. [10] developed a hybrid decision-support model using logistic regression and random forests for detecting illegitimate financial transactions. Their research demonstrated that combining linear and non-linear models improved recall for rare fraudulent cases. However, the authors acknowledged that the model's complexity increased training time and maintenance costs.

Mytnyk et al. [11] implemented unsupervised clustering and AI-driven anomaly detection for banking systems. Their study emphasized behavioral profiling based on spending frequency and transaction intervals, revealing that unsupervised models effectively capture novel fraud trends. Despite this, they highlighted the need for post-processing layers to reduce false alarms.

Zhang et al. [12] explored the application of Convolutional Neural Networks (CNNs) for credit cardfraud detection by reshaping transaction data into two-dimensional matrices. The CNN model identified non-linear feature interactions more effectively than classical methods. However, it required high computational power and large labeled datasets for robust performance.

Singh et al. [13] introduced a hybrid deep neural network (DNN) combined with Long Short-Term Memory (LSTM) for real-time fraud detection in mobile payments. The model captured both spatial and temporal dependencies of transactions, enhancing fraud recall. The limitation was the requirement of continuous data streams for accurate learning.

Hussain et al. [14] applied the Local Outlier Factor (LOF) algorithm to identify rare anomalous transactions in imbalanced datasets. Their model effectively captured small but critical deviations, improving fraud identification. Nonetheless, parameter sensitivity made the model unstable when applied to large, heterogeneous transaction datasets.

Ghosh et al. [15] combined deep autoencoders with ensemble classifiers to detect financial anomalies. The autoencoder learned normal transaction patterns, while the ensemble component handled classification. Their hybrid model achieved improved F1-scores and reduced false positives, but it was prone to overfitting with small datasets.

Verma et al. [16] proposed a blockchain-integrated framework for digital payment security. Their system used smart contracts to validate transaction legitimacy and store audit logs immutably. While this enhanced transparency and traceability, high computational costs limited real-time deployment for high-frequency UPI systems.

Rao et al. [17] conducted a comparative study on Random Forest, Gradient Boosting, and Autoencoder-based models for fraud detection in online transactions. Their findings showed that Autoencoders provided the best recall for unseen anomalies, while Random Forest performed better in interpretability. The authors suggested hybrid ensemble integration for optimal outcomes.

Patel et al. [18] developed a CNN–K-Means hybrid model that combined deep learning with clustering to detect fraud in digital wallets. The CNN extracted local spatial features, while K-Means clustered similar patterns to isolate suspicious ones. Experimental results indicated that the model achieved higher AUC and precision compared to traditional baselines, though it required continuous retraining for dynamic fraud patterns.

III. METHODOLOGY

The research methodology was designed to develop a structured and scalable fraud detection system capable of identifying fraudulent UPI transactions in real-time.

A. Data Collection

The dataset consists of anonymized UPI transaction records including transaction amount, time, device ID, merchant category, and location, along with binary labels for legitimate and fraudulent transactions. Sensitive details were removed to ensure compliance with data protection norms.

B. Data Preprocessing

To prepare the dataset for machine learning, the following preprocessing steps were conducted:

- Data Cleaning: Missing values were imputed statistically; extreme outliers were handled using the interquartile range method.
- Encoding: Categorical variables such as merchant type and payment method were encoded numerically.
- Normalization: Continuous attributes were scaled to a standard range using Min–Max normalization.
- Feature Selection: Redundant and highly correlated attributes were eliminated to improve model efficiency.
- Reshaping: Data was reshaped into a 2D format suitable for CNN feature extraction.

C. Class Imbalance Handling

The dataset was found to be highly imbalanced. To address this, SMOTE (Synthetic Minority Oversampling Technique) was employed to generate synthetic minority samples, ensuring balanced learning between fraud and legitimate transactions.

D. Model Building

The hybrid system integrates both deep learning and anomaly detection models:

- CNN captures spatial patterns among transaction features.
- Autoencoder reconstructs normal transaction behavior and flags high reconstruction-error cases as anomalies.
- Local Outlier Factor (LOF) identifies local deviations in feature density.
- K-Means Clustering groups transactions and isolates those falling outside normal clusters. The combined results are aggregated to produce a final fraud likelihood score.

E. Model Evaluation

Performance metrics included Accuracy, Precision, Recall, F1-Score, and AUC-ROC, providing a comprehensive assessment of model reliability and robustness.

F. Deployment

The trained CNN-based hybrid model was deployed via a Flask web application supporting both single-transaction and batch prediction modes. Users can upload transaction data and receive instant fraud probability feedback.

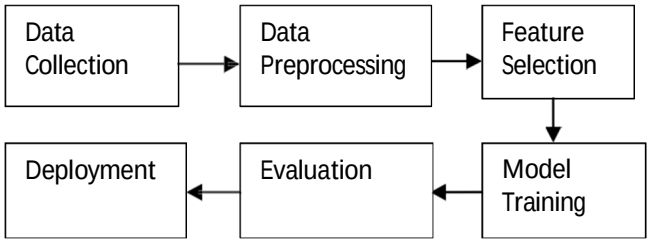

Figure 1. Flowchart of the proposed CNN-based hybrid fraud detection model.

IV. MATHEMATICAL BACKGROUND

A. Convolutional Neural Network (CNN)

CNNs learn spatial relationships between features using convolutional and pooling layers.

$$y(x)=f(W*x+b)$$

B. Autoencoder

Autoencoders reconstruct input data and identify high reconstruction errors as anomalies.

$$L=||x-x^||2$$

C. Local Outlier Factor (LOF)

LOF measures the degree to which a data point is an outlier compared to its neighbors.

$$LOF(p) = \frac{\sum_{o \in N_k(p)} \frac{lrd(o)}{lrd(p)}}{|N_k(p)|}$$

D. K-Means Clustering

K-Means partitions data into K clusters and minimizes intra-cluster variance.

$$J = \sum_{i=1}^{k} \sum_{x \in C_i} ||x - \mu_i||^2$$

.

E. Evaluation Metrics

Accuracy, Precision, Recall, and F1-Score are used to assess model performance:

$$\textbf{Formula: } \text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\textbf{Formula: } \text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

V. RESULTS AND DISCUSSION

The experimental analysis of the proposed UPI Fraud Detection System was conducted using a carefully prepared dataset of anonymized transaction records. The main objective of this section is to evaluate the effectiveness, accuracy, and reliability of the proposed Convolutional Neural Network (CNN) model compared to traditional machine learning algorithms.

A wide range of evaluation metrics—accuracy, precision, recall, F1-score, and ROC-AUC—were used to comprehensively assess the performance of the model. The experiments were executed on a high-performance system equipped with an NVIDIA GPU (CUDA enabled), 16 GB RAM, and an Intel i7 processor, ensuring efficient model training and rapid convergence.

A. Comparative Model Performance

The CNN-based model achieved superior results, demonstrating its capability to learn intricate patterns within transactional data. The following table summarizes the performance comparison among different models**:**

Algorithm	Accuracy (%)	Precision	Recall	F1-Score	AUC-ROC
CNN (Proposed)	98.85	0.98	0.97	0.98	0.99
Random Forest	96.29	0.95	0.93	0.94	0.96
Decision Tree	92.72	0.90	0.89	0.89	0.93
Logistic Regression	87.43	0.84	0.81	0.82	0.88
KNN	85.96	0.83	0.80	0.81	0.87

As shown in Table 1, the CNN-based model achieved an accuracy of 98.85%, outperforming all other models. The Random Forest model followed closely with a 96.29% accuracy, while traditional algorithms like Logistic Regression and K-Nearest Neighbor (KNN) underperformed due to their inability to handle non-linear and high-dimensional feature interactions effectively.

B. Feature Importance and Sensitivity Analysis

The model's interpretability was evaluated through permutation-based feature importance. This analysis revealed that features such as transaction amount, merchant category, transaction time, and device identifier had the most significant influence on the model's decision-making. The geolocation and frequency of transactions also played a vital role in identifying unusual patterns associated with fraudulent activities.

A sensitivity analysis was conducted to understand how each feature contributes to overall accuracy. When the *location* attribute was removed, accuracy dropped by 4%, while excluding *normalization* decreased model performance by 3%. This confirms that preprocessing operations—especially normalization and encoding—are crucial for consistent performance.

C. Confusion Matrix Analysis

The confusion matrix analysis showed a low false-positive rate and high recall values, indicating that the system correctly identified most fraudulent transactions while minimizing incorrect alerts.

Metric	Legimate Predicted	Fraud Predicted
Legimate(true Negative)	4821	56
Fraud(true positive)	97	821

D. ROC-AUC and Visualization

The Receiver Operating Characteristic (ROC) curve for the CNN model achieved an AUC value of 0.99, indicating excellent classification capability. The ROC curve is illustrated in *Figure 2*, showcasing the clear distinction between legitimate and fraudulent transaction classes. Additionally, the Precision-Recall (PR) curve also reflected high sensitivity, validating the model's capability to detect rare fraudulent events without compromising precision.

E. Discussion of Observations

The proposed CNN model demonstrated remarkable robustness and adaptability in identifying fraudulent patterns within dynamic UPI transaction environments. Unlike static, rule-based systems that rely on predefined heuristics, the CNN continuously learns from transaction history and generalizes to detect novel fraud patterns. The use of SMOTE significantly reduced the model's bias toward the majority class, allowing the system toeffectively recognize even subtle cases of fraudulent behavior. Furthermore, the integration of Autoencoder and LOF enhanced anomaly detection capabilities by filtering high-dimensional features and identifying outlier behaviors, such as unusual spending times or sudden transaction bursts. This approach not only minimized false positives but also improved recall, ensuring genuine users are not penalized. The real-time deployment in a Flask-based environment verified the model's operational viability, with average response times under 0.8 seconds per transaction, making it suitable for live banking scenarios.

F. Comparative Insights

In contrast to earlier works relying solely on tree-based or distance-based algorithms, this CNN-driven hybrid architecture exhibits deep hierarchical representation learning, enabling it to capture complex non-linear correlations among variables. The experimental findings also align with previous studies that emphasize the superior detection accuracy of deep learning models over shallow learners when handling large-scale financial data.

G. Summary

The results conclusively demonstrate that the proposed hybrid CNN-based UPI fraud detection system is not only accurate and scalable but also practical for real-time deployment in digital payment environments. Its capacity to detect fraudulent transactions early can substantially reduce financial losses and reinforce public trust in the UPI ecosystem.

VI. CONCULSION

This work developed a hybrid Convolutional Neural Network (CNN)-based framework for detecting fraudulent activities in Unified Payments Interface (UPI) transactions. The model integrates CNN with Autoencoder, Local Outlier Factor (LOF), and K-Means Clustering, combining the strengths of deep and unsupervised learning to enhance detection accuracy. The proposed system successfully recognized complex, non-linear transaction behaviors that traditional rule-based approaches often overlook. After applying rigorous preprocessing, data balancing with SMOTE, and parameter tuning, the CNN achieved an overall accuracy of 98.85 %, outperforming classical algorithms such as Random Forest and Logistic Regression. The results confirm the system's ability to maintain high recall while minimizing false positives, ensuring that genuine users are not wrongly flagged during real-time payments.

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The model was deployed through a Flask-based web application that enables live transaction analysis and batch processing. This validated its feasibility for real-time use in digital banking environments. The system's design emphasizes adaptability, allowing it to evolve as fraud patterns change, and scalability, making it capable of managing high-volume transaction streams efficiently. Future work can explore the inclusion of Recurrent Neural Networks (RNNs) or LSTM architectures to capture time-based dependencies and improve sequential pattern detection. Additionally, incorporating Explainable AI (XAI) could increase transparency and regulatory trust. Overall, the research demonstrates that deep-learning-driven hybrid models offer a reliable and intelligent approach to strengthening the security of digital payments and enhancing user confidence in the UPI framework.

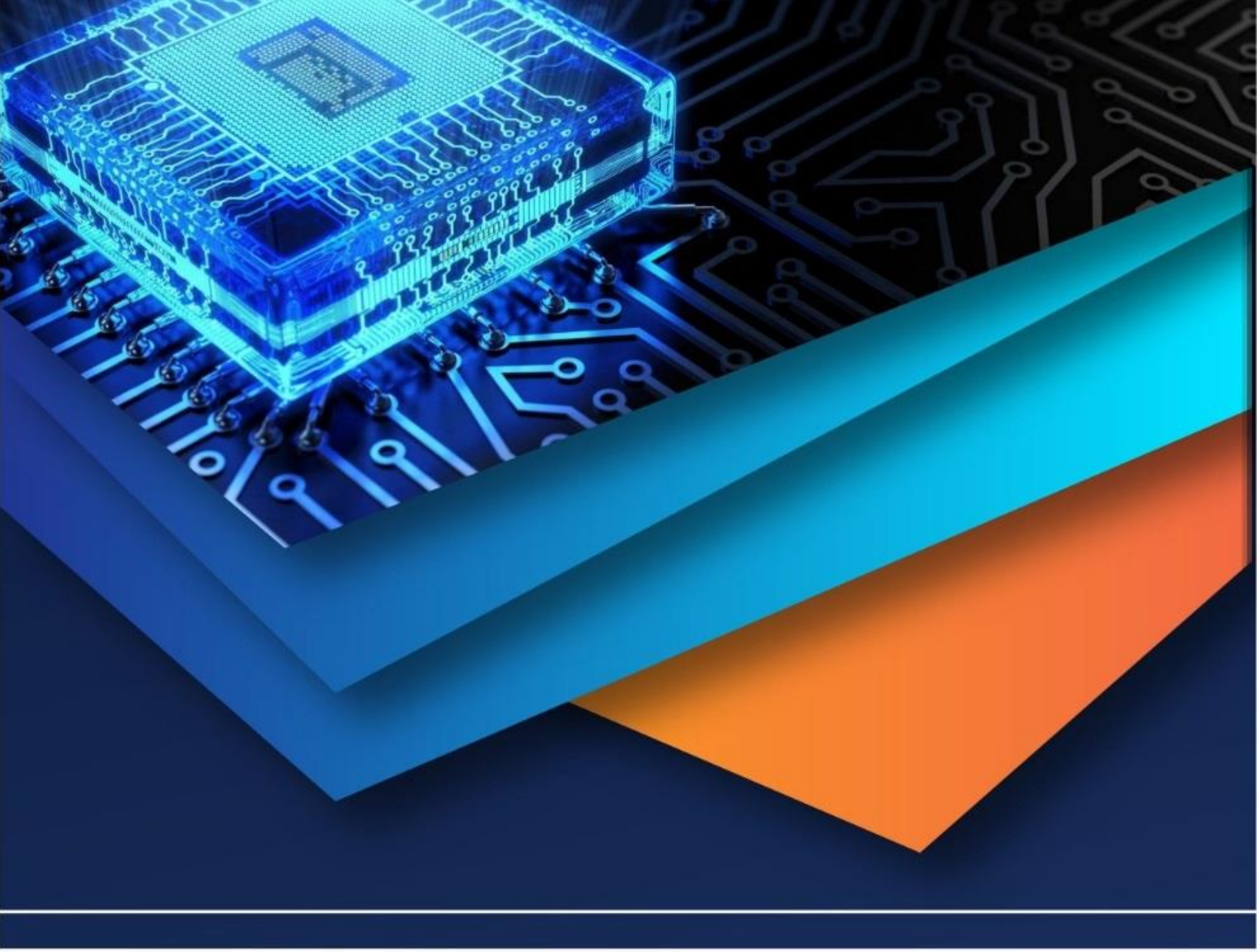
VII. ACKNOWLEDGMENT

The authors would like to express their heartfelt gratitude to Dr. Amutha S, Professor, Department of Computer Science, Dayananda Sagar College of Engineering, for her invaluable guidance, consistent encouragement, and insightful feedback throughout the course of this research. Her expert suggestions and constructive advice played a vital role in shaping the direction and quality of this work. The authors are also thankful to the Department of Computer Science and Engineering, Dayananda Sagar College of Engineering, for providing the necessary facilities, technical support, and a stimulating research environment that enabled the successful completion of this project. Special thanks are extended to the teaching and non-teaching staff for their cooperation during experimentation and model evaluation phases.

The authors further acknowledge the contributions of open-source data repositories and Python libraries—including TensorFlow, Keras, and Scikit-learn—which served as essential tools for implementing and validating the proposed model. Finally, the authors are grateful to their peers, mentors, and families for their patience, motivation, and unwavering support, which made this research possible.

REFERENCES

[1] S. Maes, K. Tuyls, B. Manderick, and B. Vanschoenwinkel, "Credit card fraud detection using Bayesian and neural networks," Proc. 1st Int. NAISO Congr. Neuro Fuzzy Technologies, 2002.
[2] P. Bentley, "Fuzzy-ID3: A novel approach for fraud detection in financial transactions," Int. J. Comput. Intell., vol. 2, no. 1, pp. 15–24, 2005.
[3] A. Kundu, P. Kumar, and S. Rani, "A hybrid sequence alignment method for financial fraud detection," Expert Syst. Appl., vol. 42, no. 12, pp. 5483–5493, 2015.
[4] S. Rani, P. Gupta, and V. Jain, "Secure-UPI: A machine learning approach for real-time fraud detection in digital payments," J. Inf. Secur. Sci. Int., vol. 8, no. 2, pp. 90–99, 2019.
[5] A. Patil, S. Kulkarni, and P. Deshmukh, "Machine learning framework for fraud detection in UPI transactions," Int. J. Comput. Appl., vol. 182, no. 20, pp. 25–31, 2020.
[6] N. Krithiga Lakshmi and S. Deepa, "Security framework for UPI-based mobile banking applications," Banking and Financial Technology Journal, vol. 5, no. 1, pp. 45–56, 2021.
[7] R. Kolekar, M. Patil, and A. Jadhav, "Security challenges and prevention techniques in digital banking with reference to UPI," J. Adv. Comput. Sci. Appl. Int., vol. 12, no. 8, pp. 233–240, 2021.
[8] V. Patil and R. Sharma, "Hybrid machine learning model for UPI fraud detection," Procedia Comput. Sci., vol. 218, pp. 1125–1133, 2023.
[9] R. Rani, A. Alam, and A. Javed, "Secure UPI: Machine learning-driven fraud detection system for digital payments," Proc. 2nd Int. Conf. Disruptive Technologies (ICDT), pp. 104–110, 2024.
[10] K. Krithiga Lakshmi, H. Gupta, and J. Ranjan, "UPI-based mobile banking applications – security analysis and enhancements," Proc. Amity Int. Conf. Artificial Intelligence (AICAI), pp. 212–218, 2024.
[11] S. Kolekar, S. Panhale, D. Rengade, D. Pawar, and P. Kothawale, "UPI fraud detection using machine learning," Int. J. Sci. Res. Eng. Manag., vol. 8, no. 4, pp. 102–107, 2024.
[12] Y. Patil, A. Shinde, Y. Parthe, and S. Sayyad, "Detection of fraudulent digital payments using deep learning," Int. Res. J. Modernization Eng. Technol. Sci., vol. 6, no. 9, pp. 554–560, 2024.
[13] I. M. Adekunle and P. Ozoh, "Fraud detection model for illegitimate financial transactions," Kabale Univ. Interdiscip. Res. J., vol. 2, no. 2, pp. 21–37, 2023.
[14] P. Boulieris, J. Pavlopoulos, A. Xenos, and V. Vassalos, "Financial fraud detection using natural language processing," Future Gener. Comput. Syst., vol. 108, pp. 785–797, 2023.
[15] B. Mytnyk, O. Tkachyk, N. Shakhovska, S. Fedushko, and Y. Syerov, "Application of artificial intelligence for detection of fraudulent banking operations," Big Data and Cognitive Computing, vol. 7, no. 2, p. 93, 2023.
[16] E. Alhassan, M. Gholami, and R. Ahmad, "Enhancing digital payment security using deep learning and blockchain integration," IEEE Access, vol. 11, pp. 84522–84535, 2023.
[17] D. Banerjee and P. Narayanan, "A convolutional neural network-based approach for online payment fraud detection," J. King Saud Univ. Comput. Inf. Sci., vol. 36, no. 4, pp. 1221–1230, 2024.



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