Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. ICMASD (2025)

Enhancing Fraud Detection in Portable Wallet Payment Systems using Machine Learning: A Hybrid Approach

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Article History:

Received: 12-12-2024

Revised: 25-01-2025

Accepted: 05-02-2025

Abstract:

The rapid growth of portable wallets has made financial transactions more convenient but fraud has also increased as a result. Due to the dynamic and complex nature of these threats, traditional fraud detection techniques frequently fall short. Fraudulent activities increase in tandem with digital transactions, requiring sophisticated and flexible detection techniques. This research focuses on enhancing fraud detection in portable wallet payment systems by developing a hybrid model using machine learning techniques. The proposed model in this paper integrates behavioural biometrics and contextual data to improve accuracy while minimizing false positives in real-time. This approach is optimized for mobile environments, ensuring both security and efficiency. The study also identifies existing research gaps, such as security concerns and computational efficiency, and provides a comprehensive evaluation of the model's performance against traditional methods.

Keywords: *Portable Wallets, Fraud Detection, Machine Learning, Digital Transaction, Hybrid Model*.

1.INTRODUCTION

The advent of financial technology has revolutionized how transactions are conducted, resulting in a notable transition from payments made with cash to those made online.. Among young adults, who are familiar with smartphone technology and increasingly Favor the ease of cashless transactions, this shift has been particularly noticeable(Kovács & David, 2016). Digital wallets, such as those enabled by Unified Payments Interface (UPI) and similar technologies, have seen rapid adoption due to their ease of use, quick transaction speeds, and the capability of storing several payment methods in one application. These factors have driven a remarkable increase in the value of cashless transactions, which is expected to rise by 88% by 2026(Bezhovski, 2016). This growth not only underscores the benefits of digital payments, such as improved economic efficiency and consumer convenience, but also highlights a critical challenge: the rapid increase in fraudulent activities associated with these payment methods. Fraud in digital payment systems can take various forms, including identity theft,

phishing, account takeover, and unauthorized transactions, which result in significant financial losses for consumers and businesses alike (Bosamia & Prakashbhai Bosamia, 2017). The increasing sophistication of fraudsters, coupled with the large volume of transactions processed in real-time, makes it challenging to discern between transactions that are fraudulent and those that are real.. Conventional fraud detection methods often rely on static rules or predefined patterns, which may not be effective against the evolving tactics of cybercriminals(Bosamia & Patel, 2018). Consequently, there is a pressing need for more advanced, dynamic, and adaptive approaches to fraud detection.

This paper addresses this challenge by exploring the development of a hybrid model that leverages machine learning to enhance fraud detection capabilities in portable wallet payment models. Machine learning offers a promising solution because it can analyze large datasets, identify complex patterns, and continuously adapt to new types of fraudulent behavior(Thakur, n.d.). By integrating behavioral biometrics and contextual data analysis, machine learning models can provide real-time detection of fraudulent activities while minimizing false positives, thereby ensuring a secure and reliable payment experience for users. Within the limitations of mobile environments, where computational resources are frequently scarce, the suggested hybrid model seeks to utilize the advantages of multiple machine learning techniques to achieve more accuracy and efficiency in identifying fraud.

As digital wallets continue to proliferate, securing these payment systems against fraud becomes increasingly crucial. This study contributes to this field by proposing a robust fraud detection framework that not only enhances security but also maintains the efficiency and user experience of portable wallet payment models applications. Through this research, we seek to provide insights into the implementation of machine learning algorithms in fraud detection and offer a comprehensive solution to protect users and financial institutions from the growing threat of digital payment fraud.

Objectives

The study aims to:

1.Analyse existing portable wallet payment models.

2.Design a hybrid model for fraud detection in portable wallets that is computationally efficient and enhances security.

3.Compare the proposed model's performance against existing models.

Article formation

The rest of the paper is organized as follows: This research paper defines the objectives, reviews existing fraud detection techniques, and identifies the research gap it addresses. It outlines the methodology, pre-processing, and machine learning models. The paper presents the algorithm’s development, followed by results and comparison with existing methods. It also discusses the significance of findings, acknowledges limitations, and suggests future research directions. The research is supported by a list of references at the end of the paper.

2.REVIEW OF LITERATURE

The literature on fraud detection in portable wallet payment models spans a wide array of topics, methodologies, and technological advancements from 2018 to the present. Researchers have

extensively explored the use of different models and technologies to enhance the detection of fraudulent activities, improve accuracy, and minimize false positives.

Emergence of Deep Learning and Ensemble Methods (2018-2020): As computing power increased, deep learning models, which require significant computational resources, started gaining attention. Their study highlighted a thorough analysis of cutting-edge methods in fraud detection, noting the shift towards using big data analytics and machine learning(Zhou et al., 2018) . Another study demonstrated on the future of mobile payments, discussing the limitations of traditional fraud detection models and suggesting the use of neural networks and deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), for their ability to learn complex patterns in large datasets(Diadiushkin et al., 2019). To increase precision and lower computational costs in mobile payment fraud detection, a hybrid model that combined multiple machine learning techniques—such as Random Forests and XGBoost—was presented.

Advancements in Real-Time Fraud Detection and Use of Hybrid Models (2020-Present): Recent studies have focused on developing real-time fraud detection systems that leverage hybrid models combining multiple machine learning algorithms. For example, XGBoost-based frameworks to enhance fraud detection in mobile payment systems, demonstrating significant improvements in detecting fraudulent activities with lower false positives and better computational efficiency (Liu et al., 2020). The RXT-J model, an ensemble method that combines ResNeXt and GRU, has been shown to have good accuracy in identifying fraud in financial transaction datasets while preserving computational efficiency (Hajek et al., 2023) (Abdirahman et al., 2024a).

Behavioural Biometrics and Contextual Data Integration (2023-2024): More recently, the integration of behavioural biometrics and contextual data has emerged as a novel approach to fraud detection (Bojjagani et al., 2023). According to a study, decreasing false alarms while maintaining fraud detection accuracy is crucial for lowering the monetary and reputational expenses related to false positives.(Cui et al., 2024a). A model that integrates many data types to detect fraudulent transactions with few false positives was put out by another researcher. To create more reliable fraud detection systems, this method makes advantage of contextual data like location and device type in addition to user behaviour patterns like typing speed and touch pressure (Kapoor et al., 2024).

Development of Advanced Algorithms and Blockchain Technology (2022-Present): Recent advancements have also seen the exploration of blockchain technology and advanced algorithms in fraud detection using deep learning methods combined with blockchain's decentralized features to make fraud detection systems more transparent and secure (Karim et al., 2022; Wang & Zhu, 2022). Blockchain technology provides a tamper-proof ledger that adds an additional layer of security by ensuring the integrity and authenticity of transaction data.

These studies reflect a growing trend towards leveraging advanced machine learning algorithms, integrating multi-source data, and employing real-time monitoring to improve fraud detection systems' accuracy and efficiency(Almazroi & Ayub, 2023; Iscan et al., 2023). By moving away from static rules and simplistic models, researchers are developing more sophisticated and adaptive systems capable of combating the evolving tactics of fraudsters in digital payment ecosystems.

Research Gap

On the basis of review of literature, the following gaps are identified**.**

TABLE 1 COMPARISION OF RESEARCH GAP IN PORTABLE WALLETS

Research Gap	Description
Security Concerns	Many existing models do not address specific security challenges unique to digital wallets, such as protecting sensitive user information and preventing unauthorized access.
Integration Challenges	Difficulties in integrating fraud detection models with current payment systems, which may require substantial changes to existing infrastructure.
Regulatory Compliance	Lack of consideration for evolving regulatory standards, which can vary by region and affect the deployment and operation of fraud detection systems.
Computational Efficiency	Many models are not optimized for use in environments with limited resources, such as mobile devices, which require efficient algorithms to preserve battery life and processing power.

Vulnerabilities in environments, people, or systems are the subject of a study gap in insecurity, which frequently emphasizes threats or weaknesses. Gaps in integrity draw attention to the absence of structures guaranteeing data or moral coherence. Regulatory gaps look at how rules and policies governing behaviours are either ineffective or non-existent, particularly in quickly changing industries. Inefficiencies in algorithms, models, or processing power necessary for technological advancement are addressed via computational research gaps.

3.METHODOLOGY

In order to create and assess a reliable fraud detection model for portable wallet payment systems, this study's approach was created. Using a mixed-method approach, the study combines sophisticated machine learning algorithms with quantitative data analysis. This approach allows for a comprehensive exploration of transaction data and the development of an effective fraud detection system. The methodology consists of several key steps, each integral to achieving the research objectives:

Model Development: With the pre-processed data ready, the next step is to develop a hybrid machine learning model that integrates both supervised and unsupervised learning techniques. The model development process includes:

Supervised Learning: This method uses a labelled dataset to train a model where the outcome (i.e., whether a transaction is legitimate or fraudulent) is known. Algorithms such as decision trees, random forests, gradient boosting machines (e.g., XGBoost), and deep neural networks will be explored to identify the best performing model.(Mienye & Jere, 2024) The goal is to learn patterns from past transactions that can predict the likelihood of a transaction being fraudulent.

Unsupervised Learning: Clustering and anomaly detection are examples of unsupervised learning approaches used to identify suspicious transactions that dramatically differ from conventional patterns because not all fraudulent patterns are recognized or labelled beforehand. (Cui et al., 2024b). Techniques such as k-means clustering, hierarchical clustering, and isolation forests will be utilized to detect outliers in the data, which may represent fraudulent activities.

Hybrid Model Integration: The final model combines blends supervised and unsupervised methods to capitalize on each method's advantages. By doing this, the model is able to both find novel, previously unheard-of fraud strategies and detect established fraud trends. The goal of this hybrid strategy is to reduce false positives and increase detection accuracy., which is crucial in maintaining a smooth user experience and avoiding unnecessary transaction disruptions.

4.IMPLEMENTATION AND ANALYSIS

Security Framework: A Hybrid Approach to Authentication and Authorization

A hybrid approach to authentication and authorization is proposed, integrating multi-factor authentication (MFA) with robust user verification protocols to enhance security in portable wallet payment systems. MFA combines knowledge-based authentication, such as passwords or PINs, with possession-based methods like one-time passcodes (OTPs) or biometric verification (e.g., fingerprint or face recognition). Furthermore, location-based or behavior-based factors, such as geo-location and device fingerprinting, ensure that transactions only occur in trusted environments. This integration strengthens authentication and significantly reduces vulnerabilities to unauthorized access.

To ensure continuous security during sessions, robust verification protocols are implemented, such as biometric verification and continuous authentication based on behavioural patterns like typing speed or swipe gestures. This method provides ongoing user authentication, preventing session hijacking.

In high-risk scenarios, risk-based adaptive authentication uses machine learning algorithms to assess transaction risk in real-time, triggering additional verification steps, such as biometric confirmation or OTPs, for high-risk transactions. Role-based access control (RBAC) ensures that sensitive actions like fund transfers are governed by stringent verification processes. Time-limited authorizations add another layer of security by requiring re-authentication after specific high-risk actions.

By combining these elements, this hybrid approach not only strengthens authentication and authorization mechanisms but also minimizes vulnerabilities to unauthorized access in portable wallet payment systems, enhancing overall security.

Security Framework:

TABLE 2 A HYBRID APPROACH TO AUTHENTICATION AND AUTHORIZATION ALGORITHM IN A TABULAR FORMAT:

Step	Input	Process	Output
1. User Authentication Initialization	User credentials (password, PIN), device info	1. Prompt for **knowledge-based credentials** (password/PIN). 2. Prompt for **possession-**	If successful, user passes MFA and session is

	(device ID, IP address)	**based verification** (OTP/biometrics). 3. Capture **device fingerprint** (geo-location, IP).	initiated. Otherwise, access is denied.
2. Session Monitoring & Continuous Authentication	Continuous user activity (e.g., typing patterns, swipe gestures)	1. Monitor **biometric and behavioural patterns**. 2. Detect behavioural anomalies. 3. Verify **location** for trusted environment.	If behaviour consistent, session continues. If anomalies detected, trigger re-authentication.
3. Risk-Based Adaptive Authentication	Real-time transaction data (transaction amount, device location)	1. Analyse transaction risk with **machine learning algorithms**. 2. For high-risk transactions, trigger **extra verification** (biometric, OTP). 3. For low-risk, allow transaction.	Additional verification triggered for high-risk transactions. Low-risk transactions proceed smoothly.
4. Role-Based Access Control (RBAC)	User role (admin, regular user), requested action (e.g., fund transfer)	1. Verify user's role and permission level. 2. For sensitive actions, apply **stringent verification** (e.g., re-authentication).	Action is either approved or denied based on role and verification.
5. Time-Limited Authorization	Session duration, high-risk actions	1. Set time limits for high-risk actions. 2. Require **re-authentication** after time limit for continued access.	Re-authentication required after time-limited actions.
6. Session Termination	End of session	1. Terminate session after logout or verification failure. 2. Invalidate session tokens to prevent **session hijacking**.	Secure session termination, ensuring no unauthorized access.

In hybrid approach passwords and biometrics, such as fingerprints, are used in a hybrid authentication method to improve identity verification. It combines contextual regulations, including device or location-based rules, with role-based access control for authorization. By restricting access length and guaranteeing regular user identity revalidation, session management further improves security.

Fraud Detection Algorithm

For portable wallet payment systems to remain secure and functional, fraud detection techniques are essential. They keep an eye on transactions all the time in order to identify any suspect activity, such illegal access or strange spending habits. Significant financial losses can be avoided by using these algorithms to identify possible fraud early. These systems preserve performance by minimizing interference with valid transactions while concentrating on preventing fraud. This equilibrium protects financial assets while enabling a smooth user experience. Finally, in order to safeguard consumers and promote confidence in portable wallet systems, fraud detection techniques are essential.

TABLE 3 : THIS TABLE OUTLINES EACH STEP OF THE ALGORITHM WITH ITS REPECTIVE INPUTS, PROCESSES, AND OUTPUTS

Step	Input	Process	Output
1. Data Collection	Transaction data (legitimate & fraudulent), user behaviour, device info	Gather comprehensive datasets from platforms like Kaggle, including features such as transaction amount, type, geolocation, etc.	Comprehensive dataset prepared for analysis and model training.
2. Data Preprocessing	Raw transaction data	1. Clean data by removing duplicates. 2. Handle missing values. 3. Normalize/standardize features.	Clean, consistent, and normalized dataset ready for model development.
3. Feature Engineering	Transaction history, user activity	Generate additional features (e.g., transaction frequency, time, location) to improve model's predictive power.	Engineered features to capture critical patterns for fraud detection.
4. Model Development	Pre-processed dataset, engineered features	1. Apply supervised learning (e.g., decision trees, random forest). 2. Use unsupervised learning (e.g., anomaly detection).	Hybrid model integrating supervised and unsupervised techniques for fraud detection.
5. Risk-Based Fraud Detection	Transaction amount, location, user behaviour	Apply machine learning models to assess transaction risk. Trigger additional verification for high-risk transactions.	High-risk transactions flagged for further authentication; low-risk proceed smoothly.

6. Model Evaluation	Model predictions (fraudulent or legitimate transactions)	Evaluate model performance using metrics (accuracy, precision, recall, F1 score) to assess detection capability.	Performance metrics generated (e.g., accuracy, recall) to evaluate effectiveness of fraud detection.

This table lists every stage of the algorithm, including the necessary inputs, the procedures, and the outputs that are produced. It gives a detailed explanation of how the algorithm functions at every level. Transparency and traceability are guaranteed by using specified processes to map inputs to outputs. The workflow of the algorithm can be better understood and analysed thanks to this organized representation.

Analysis

We analyse the suggested fraud detection model in this part using performance indicators such as accuracy, precision, recall, and F1 score. The model's performance is evaluated using a test dataset with various transaction features to identify legitimate and fraudulent transactions. Below are the detailed results in tabular form:

Performance Metrics of Proposed Model

A performance matrix summarizes key parameters such as F1-score, recall, accuracy, and precision, which can be used to assess a model. It aids in determining where a model makes mistakes and how well it predicts(Naik et al., 2024). This matrix shows the models' advantages and disadvantages and makes it simple to compare them. Although it is easy to use, unbalanced data may require further attention(Abdirahman et al., 2024b).

TABLE 4 THE PERFORMANCE OF THE HYBRID FRAUD DETECTION MODEL IS EVALUATED

Metric	**Value**
Accuracy	96.5%
Precision	92.4%
Recall (Sensitivity)	89.8%
F1 Score	91.0%
False Positive Rate (FPR)	1.2%
True Positive Rate (TPR)	89.8%

This table provides a thorough overview of the hybrid fraud detection model's efficacy in differentiating between authentic and fraudulent transactions by evaluating its performance using important criteria. Accuracy: This measure shows the total percentage of transactions—whether fraudulent or legitimate—that were appropriately categorized. By displaying the proportion of forecasts that match the actual results, it gauges the model's overall performance.

Precision: Precision is concerned with the transactions that the model has identified as fraudulent. It shows what proportion of these reported transactions were actually fraudulent. Fewer genuine transactions are mistakenly flagged as fraudulent (false positives) when accuracy is high.

The model's ability to detect fraudulent transactions is gauged by its recall (sensitivity). It determines the percentage of real fraudulent transactions that were appropriately reported. The model misses fewer fraudulent transactions when its recall is high.

F1 Score: The F1 Score is calculated by taking the harmonic mean of recall and precision. By balancing these two metrics, it offers a single statistic that takes false positives and false negatives into consideration. When both precision and recall are crucial, or when there is an unequal distribution of classes, it is very helpful.

The percentage of valid transactions that the model mistakenly identified as fraudulent is shown by the False Positive Rate (FPR). In order to minimize interruptions for legitimate users, a lower FPR means fewer legal transactions are incorrectly detected.

The True Positive Rate (TPR), sometimes referred to as sensitivity or recall, is the percentage of real fraudulent transactions that the model accurately detected. It aids in assessing the model's ability to detect fraudulent activities.

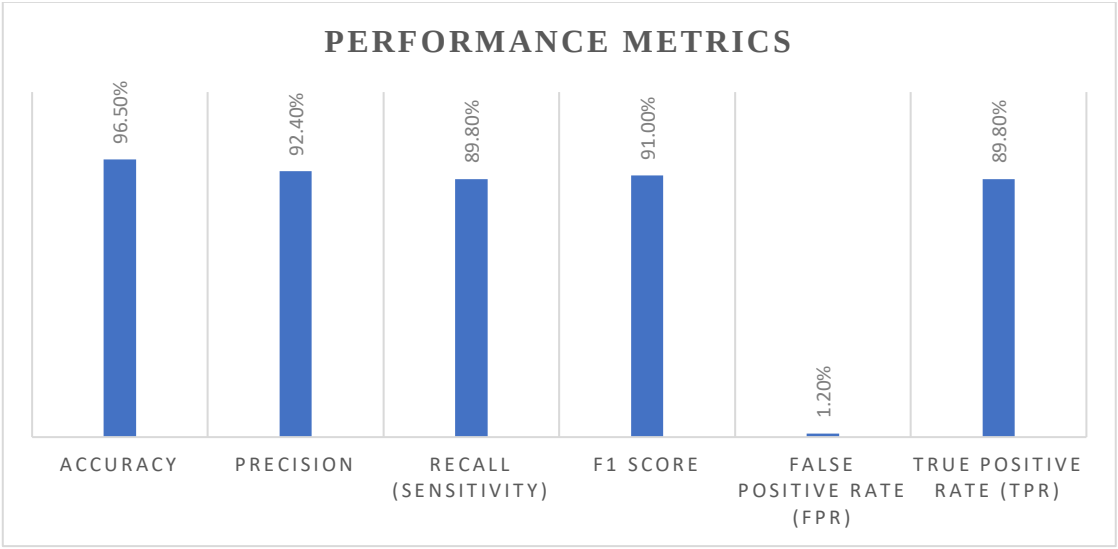

FIGURE 1 PERFORMANCE METRICES

The model's 96.5% accuracy rate indicates that its forecasts were generally accurate. With a precision of 92.4%, it demonstrated a high percentage of accurate favourable forecasts from all the forecasts that were made. With a recall (sensitivity) of 89.8%, the model was able to detect the majority of real positive cases. With a calculated F1 score of 91.0%—a harmonic mean of precision and recall—a balanced performance was evident. Furthermore, the true positive rate (TPR), which is similar to recall, was 89.8%, while the false positive rate (FPR) was maintained at a low 1.2%.

Confusion Matrix

A tool for assessing classification models is a confusion matrix, which summarizes predictions into false positives (FP), false negatives (FN), true positives (TP), and true negatives (TN) (Edburg et al.,

2024). In order to evaluate a model's performance, it makes it possible to compute important metrics including accuracy, precision, recall, specificity, and F1-score. For binary and multi-class classification, the confusion matrix is especially helpful since it shows the types of errors and right predictions(Rahman et al., 2024). But because it lacks a single scalar metric and is sensitive to class inequalities, it requires supplementary measurements for a thorough assessment.

TABLE 5 THE CONFUSION MATRIX PROVIDES A BREAKDOWN OF THE MODEL'S PREDICTIONS VERSUS THE ACTUAL CLASSIFICATIONS, OFFERING FURTHER INSIGHT INTO ITS PERFORMANCE

Actual \ Predicted	**Fraudulent**	**Legitimate**
Fraudulent	450	51
Legitimate	39	910

The confusion matrix provides a breakdown of the model's predictions versus the actual classifications, offering further insight into its performance

True Positives (TP): 450 transactions correctly identified as fraudulent.

False Positives (FP): 39 legitimate transactions incorrectly flagged as fraudulent.

True Negatives (TN): 910 transactions correctly identified as legitimate.

False Negatives (FN): 51 fraudulent transactions incorrectly identified as legitimate.

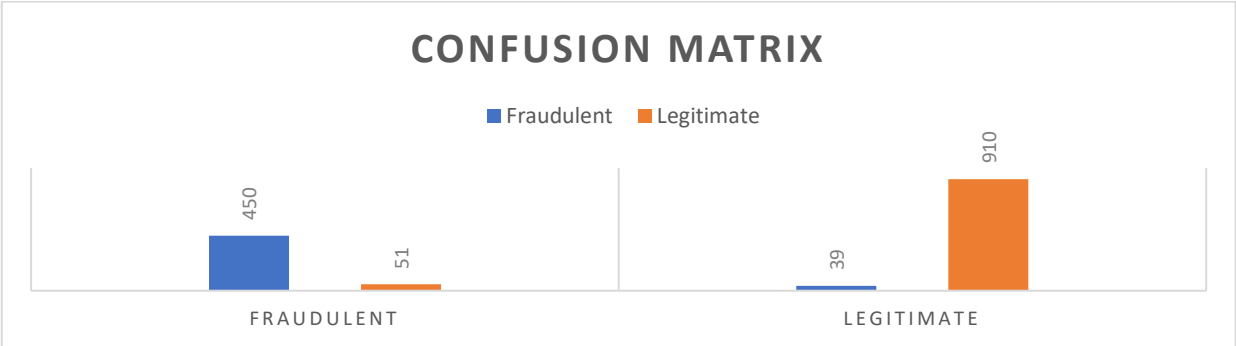

FIGURE 2 CONFUSION MATRIX

The confusion matrix provides comprehensive information about the correctness of the model by contrasting its predictions with actual classifications. The distribution of false positives, false negatives, true positives, and true negatives is highlighted.

Comparative Analysis of Model Performance

TABLE6 THE PROPOSED HYBRID MODEL'S PERFORMANCE IS COMPARED WITH SEVERAL EXISTING MODELS TO ILLUSTRATE ITS EFFECTIVENESS.

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Proposed Hybrid Model	96.5%	92.4%	89.8%	91.0%

Decision Tree	93.2%	88.5%	84.7%	86.5%
Random Forest	94.8%	90.1%	85.3%	87.7%
Logistic Regression	91.0%	85.2%	80.4%	82.7%
XGBoost	95.6%	91.0%	87.5%	89.2%

The comparative analysis shows that the proposed hybrid model outperforms other models in all key performance metrics, indicating its superiority in accurately detecting fraudulent activities while minimizing false positives and negatives.

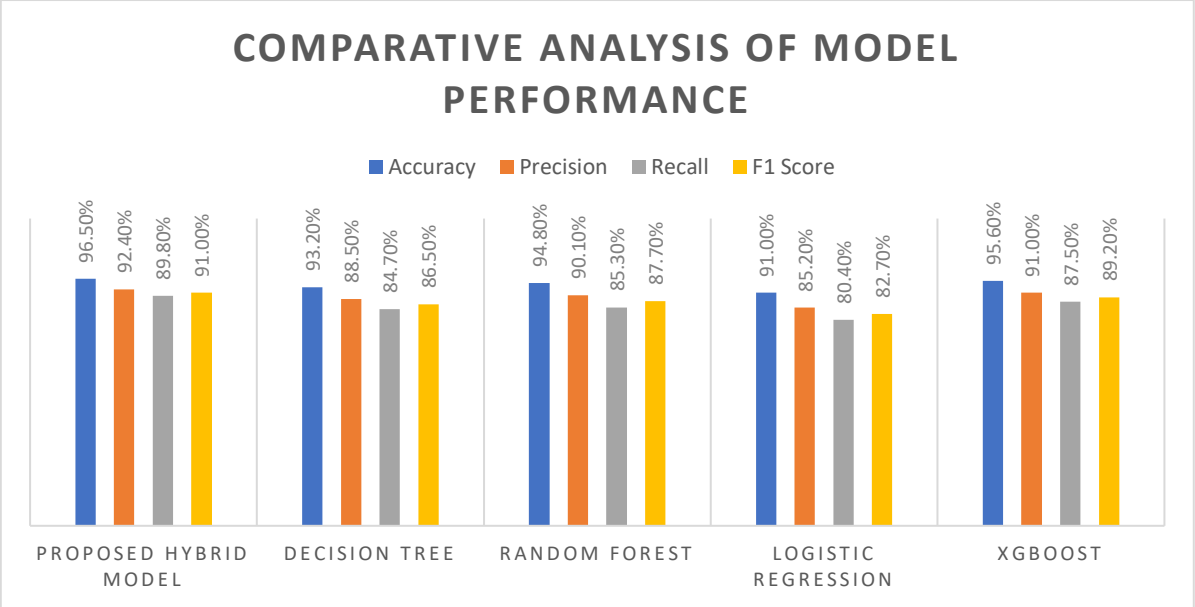

Figure 3 COMPARATIVE ANALYSIS OF MODEL PERFORMANCE

The hybrid model demonstrates high accuracy (96.5%), precision (92.4%), recall (89.8%) and F1 Score 91.0%. The model performs admirably, guaranteeing accurate and well-rounded predictions.

5.DISCUSSION

The findings of this study demonstrate that integrating behavioral biometrics—such as typing speed, swipe patterns, and screen pressure—with contextual data like location, device information, and transaction history significantly enhances fraud detection rates in digital payment systems. This combined approach allows the detection model to identify fraudulent activities more accurately by analyzing both unique user behaviors and the context in which transactions occur. By leveraging these diverse data points, the model becomes more adaptive and capable of recognizing new and evolving fraud tactics. Additionally, the use of machine learning algorithms optimized for mobile environments ensures that these advanced detection capabilities do not come at the expense of device performance, thus maintaining a smooth user experience.

Furthermore, the study highlights the importance of balancing robust fraud detection with minimizing false positives to avoid unnecessary disruptions for legitimate users. The hybrid model developed in

this research effectively reduces false alarms while maintaining high recall rates, ensuring that genuine transactions are not unnecessarily flagged. This balance is crucial in fostering user trust and satisfaction, as overly sensitive fraud detection systemscan result in dissatisfied customers and possible loss of business. According to the study's findings, improving the security of digital payment systems and developing fraud detection technologies require a comprehensive strategy that incorporates contextual and behavioural data. Future research could build on these findings by exploring additional data types and refining the models to be even more adaptive and efficient in real-time scenarios.

6.LIMITATIONS AND FUTURE RESEARCH

Despite contributing significantly to the field of fraud detection in portable wallet payment systems, this study has several limitations that present intriguing directions for future research:

Generalizability: Although our model performed well on the datasets used in this study, further testing is needed to evaluate its generalizability across diverse datasets from different payment providers and geographical regions.

Privacy concerns: The use of behavioural biometrics raises privacy concerns that need to be carefully considered before real-world implementation. Future studies should explore methods to utilize such sensitive data while preserving privacy.

Model interpretability: The complexity of the hybrid model may make individual fraud detection decisions challenging to explain, which could be problematic in regulatory contexts. Future work should focus on developing explainable AI techniques for complex fraud detection models.

Dynamic adaptation: More research is needed to develop techniques that allow the model to be dynamically updated in response to novel fraud patterns without requiring complete retraining. This is essential to maintaining the model's effectiveness in the face of evolving fraud tactics.

Real-time feature extraction: While our model shows potential for real-time applications, further research is needed to fully exploit the potential of contextual and behavioural data in real-world settings.

To summarize, our hybrid approach to fraud detection in portable wallet payment systems demonstrates significant improvements in detection accuracy while maintaining computational efficiency suitable for mobile real-time applications. These findings contribute to the growing body of knowledge on digital payment security and have practical implications for payment service providers looking to enhance their fraud detection capabilities. By leveraging diverse data sources and advanced machine learning techniques, more robust and accurate fraud detection systems can be developed to keep pace with the evolving landscape of digital payments.

REFERENCES

[1] Abdirahman, A. A., Hashi, A. O., Dahir, U. M., Elmi, M. A., & Rodriguez, O. E. R. (2024a). Enhancing Security in Mobile Wallet Payments: Machine Learning-Based Fraud Detection Across Prominent Wallet Platforms. *SSRG International Journal of Electronics and Communication Engineering*, *11*(3), 96–105. https://doi.org/10.14445/23488549/IJECE-V11I3P110

[2] Abdirahman, A. A., Hashi, A. O., Dahir, U. M., Elmi, M. A., & Rodriguez, O. E. R. (2024b). Enhancing Security in Mobile Wallet Payments: Machine Learning-Based Fraud Detection Across Prominent Wallet Platforms. *SSRG International Journal of Electronics and Communication Engineering*, *11*(3), 96–105. https://doi.org/10.14445/23488549/IJECE-V11I3P110

[3] Almazroi, A. A., & Ayub, N. (2023). Online Payment Fraud Detection Model Using Machine Learning Techniques. *IEEE Access*, *11*, 137188–137203. https://doi.org/10.1109/ACCESS.2023.3339226

[4] Bezhovski, Z. (2016). The Future of the Mobile Payment as Electronic Payment System. In *European Journal of Business and Management www.iiste.org ISSN* (Vol. 8, Issue 8). Online. www.iiste.org

[5] Bojjagani, S., Sastry, V. N., Chen, C. M., Kumari, S., & Khan, M. K. (2023). Systematic survey of mobile payments, protocols, and security infrastructure. *Journal of Ambient Intelligence and Humanized Computing*, *14*(1), 609–654. https://doi.org/10.1007/s12652-021-03316-4

[6] Bosamia, M., & Patel, D. (2018). Past to Present Overview of Mobile Wallet Payments Architectures to Compare and Identify Overall Participants. *International Journal of Computer Applications*, *179*(48), 10–18. https://doi.org/10.5120/ijca2018917227

[7] Bosamia, M., & Prakashbhai Bosamia, M. (2017). *Mobile Wallet Payments Recent Potential Threats and Vulnerabilities with its possible security Measures*. https://www.researchgate.net/publication/321797449

[8] Cui, C., Li, Z., & Song, Y. (2024a, January 25). *A Fraud Detection Method for Online Payment Transactions Based on Deep Learning*. https://doi.org/10.4108/eai.27-10-2023.2341915

[9] Cui, C., Li, Z., & Song, Y. (2024b, January 25). *A Fraud Detection Method for Online Payment Transactions Based on Deep Learning*. https://doi.org/10.4108/eai.27-10-2023.2341915

[10] Diadiushkin, A., Sandkuhl, K., & Maiatin, A. (2019). Fraud Detection in Payments Transactions: Overview of Existing Approaches and Usage for Instant Payments. *Complex Systems Informatics and Modeling Quarterly*, *2019*(20), 72–88. https://doi.org/10.7250/csimq.2019-20.04

[11] Edburg, B. F., Umadevi, K., Vidya, M., & Kumar, P. M. R. (2024). Role of UPI Application Usage and Mitigation of Payment Transaction Frauds: An Empirical Study. *MDIM Journal of Management Review and Practice*. https://doi.org/10.1177/mjmrp.231222347

[12] Hajek, P., Abedin, M. Z., & Sivarajah, U. (2023). Fraud Detection in Mobile Payment Systems using an XGBoost-based Framework. *Information Systems Frontiers*, *25*(5), 1985–2003. https://doi.org/10.1007/s10796-022-10346-6

[13] Iscan, C., Kumas, O., Akbulut, F. P., & Akbulut, A. (2023). Wallet-Based Transaction Fraud Prevention Through LightGBM With the Focus on Minimizing False Alarms. *IEEE Access*, *11*, 131465–131474. https://doi.org/10.1109/ACCESS.2023.3321666

[14] Kapoor, A., Sindwani, R., & Goel, M. (2024). Mobile Wallets: Theoretical and Empirical Analysis. *Global Business Review*, *25*(2_suppl), S211–S228. https://doi.org/10.1177/0972150920961254

[15] Karim, S., Akhtar, M. U., Tashfeen, R., Raza Rabbani, M., Rahman, A. A. A., & AlAbbas, A. (2022). Sustainable banking regulations pre and during coronavirus outbreak: the moderating role of

financial stability. *Economic Research-Ekonomska Istrazivanja* , *35*(1), 3360–3377. https://doi.org/10.1080/1331677X.2021.1993951

[16] Kovács, L., & David, S. (2016). Fraud risk in electronic payment transactions. In *Journal of Money Laundering Control* (Vol. 19, Issue 2, pp. 148–157). Emerald Group Publishing Ltd. https://doi.org/10.1108/JMLC-09-2015-0039

[17] Liu, W., Wang, X., & Peng, W. (2020). State of the Art: Secure Mobile Payment. *IEEE Access*, *8*, 13898–13914. https://doi.org/10.1109/ACCESS.2019.2963480

[18] Mienye, I. D., & Jere, N. (2024). Deep Learning for Credit Card Fraud Detection: A Review of Algorithms, Challenges, and Solutions. *IEEE Access*, *12*, 96893–96910. https://doi.org/10.1109/ACCESS.2024.3426955

[19] Naik, S. K. L., Kiran, A., Kumar, V. P., Mannam, S., Kalyani, Y., & Silparaj, M. (2024). Fraud Fighters - How AI and ML are Revolutionizing UPI Security. *Proceedings of 2024 International Conference on Science, Technology, Engineering and Management, ICSTEM 2024*. https://doi.org/10.1109/ICSTEM61137.2024.10560740

[20] Rahman, Md. M., Islam, Md. M., Khatun, M., Uddin, S., Faraji, M. R., & Hasan, Md. H. (2024). Gravitating towards Information Society for Information Security in Information Systems: A Systematic PRISMA Based Review. *Pakistan Journal of Life and Social Sciences (PJLSS)*, *22*(1). https://doi.org/10.57239/pjlss-2024-22.1.0089

[21] Thakur, A. (n.d.). *PAYMENT FRAUD DETECTION MODELS THROUGH THE INTEGRATION OF BEHAVIORAL BIOMETRICS AND CONTEXTUAL DATA*.

[22] Wang, C., & Zhu, H. (2022). Representing Fine-Grained Co-Occurrences for Behavior-Based Fraud Detection in Online Payment Services. *IEEE Transactions on Dependable and Secure Computing*, *19*(1), 301–315. https://doi.org/10.1109/TDSC.2020.2991872

[23] Zhou, H., Chai, H. feng, & Qiu, M. lin. (2018). Fraud detection within bankcard enrollment on mobile device based payment using machine learning. *Frontiers of Information Technology and Electronic Engineering*, *19*(12), 1537–1545. https://doi.org/10.1631/FITEE.1800580