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Technology Integration for Electronic Fraud Mitigation in Third-Party Payment Channels

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Abstract**—Electronic transactions have become a cornerstone of global commerce in the digital era, necessitating robust security measures to counter increasingly sophisticated fraud techniques. This research explores various methodologies to detect and prevent fraud in third-party payment channels, which have grown in complexity alongside technological advancements. The study evaluates traditional rule-based systems, machine learning algorithms, and behavioral analytics to identify fraudulent activities in electronic transactions. By integrating these methods, the research aims to create a comprehensive fraud detection system that balances accuracy, precision, and recall. Experimental results demonstrate that while machine learning models excel in detecting fraud, combining different detection methods can enhance security measures. This study provides insights into the current landscape of fraud detection technologies and offers recommendations for improving the effectiveness of these systems to safeguard electronic transactions against evolving threats.**

Index Terms—Fraud Detection, Electronic Transactions, Machine Learning, Payment.

I. INTRODUCTION

In the digital age, electronic transactions have become the backbone of modern commerce, enabling seamless and instantaneous financial exchanges across the globe [1] [2] [3]. As the reliance on third-party payment channels—such as PayPal, Stripe, and various digital wallets—grows, so does the complexity of ensuring secure transactions [4] [5] [6]. Despite technological advances, these platforms are increasingly targeted by malicious actors seeking to exploit vulnerabilities for fraudulent purposes. The sophistication of fraud techniques has evolved alongside technological advancements, making traditional detection methods inadequate [7] [8] [9].

Fraud in electronic transactions encompasses a range of deceptive practices designed to exploit vulnerabilities in digital financial systems [9] [10]. As the volume and complexity of electronic transactions have grown, so too have the tactics employed by fraudsters [11] [12] [13]. These fraudulent activities can lead to substantial financial losses for both consumers and businesses, necessitating robust security measures and fraud detection systems [14].

Fraud detection in electronic transactions is a critical challenge that involves identifying and mitigating unauthorized or malicious activities while maintaining a smooth user experience [15] [16].

This paper explores the multifaceted approach required to address fraud in third-party payment channels, focusing on the technologies, methodologies, and strategies employed to safeguard financial transactions. By examining current practices and emerging trends, this paper aims to provide a comprehensive overview of fraud detection and offer insights into enhancing security measures.

II. REVIEW OF LITERATURE

A. Electronic Transaction

Electronic transactions, or e-transactions, encompass a wide range of financial activities conducted via electronic means rather than physical exchange [17] [18]. This category includes various forms of payment and money transfers executed over the Internet or other digital platforms. The rise of e-commerce and digital financial services has significantly increased electronic transactions, transforming how individuals and businesses conduct financial operations [19] [20].

These transactions typically involve the transfer of funds from one party to another using digital tools such as online banking, mobile payment apps, and digital wallets. Key types of electronic transactions include credit card payments, debit card transactions, direct bank transfers, and peer-to-peer payment systems [21] [22] [23]. The convenience and efficiency of electronic transactions have made them the preferred method of payment for many, supporting the rapid growth of online shopping and digital financial services [24] [25] [26].

B. Third-Party Payment Channels

Third-party payment channels refer to intermediaries that facilitate transactions between buyers and sellers, offering a layer of security and convenience [27] [28] [29]. These platforms manage the payment process, handle the transfer of funds, and often provide additional features such as fraud protection, transaction dispute resolution, and integration with other financial services [30] [31].

The role of third-party payment channels is to streamline the transaction process by acting as a bridge between the payer and the payee. They handle the authentication, authorization, and settlement of transactions, reducing the need to exchange financial information between parties directly. This intermediary role enhances security by masking sensitive financial data and implementing additional safeguards against fraud.

C. Benefits and Risks

The adoption of third-party payment channels offers several benefits, including increased convenience, enhanced security, and simplified transaction management. For businesses, these platforms provide easy integration with existing e-commerce systems, enabling quick setup and access to a broad customer base [24] [32] [33]. For consumers, the convenience of making payments with a few clicks or taps, coupled with features such as purchase protection and transaction tracking, adds to the appeal of these services [34] [35].

However, the use of third-party payment channels also introduces certain risks. These platforms can be attractive targets for fraudsters seeking to exploit payment process vulnerabilities. The complexity of managing multiple payment systems and ensuring compliance with various regulations further complicates the security landscape [36] [37]. Thus, while third-party payment channels offer significant advantages, they also necessitate robust fraud detection and prevention measures to safeguard against potential threats.

D. Electronic Fraud

Fraud in electronic transactions encompasses a range of deceptive practices designed to exploit vulnerabilities in digital financial systems [38] [39]. As the volume and complexity of electronic transactions have grown, so too have the tactics employed by fraudsters. These fraudulent activities can lead to substantial financial losses for both consumers and businesses, necessitating robust security measures and fraud detection systems [40] [7].

1) Common Fraud Schemes:

- Phishing and Social Engineering: Phishing is a deceptive practice where fraudsters use fraudulent emails, messages, or websites to trick individuals into divulging sensitive information such as passwords or credit card numbers [41] [42] [43]. These communications often appear to come from legitimate organizations, such as banks or payment processors. Social engineering, a broader term, includes various manipulative tactics to persuade individuals to disclose confidential information or perform actions that compromise security [44] [45].

- Account Takeover: Account takeover occurs when a fraudster gains unauthorized access to a user's account, typically by obtaining login credentials through phishing or data breaches [46] [47]. Once in control, the fraudster can make unauthorized transactions, change account details, or access sensitive information. This type of fraud is particularly concerning in scenarios involving online banking and e-commerce platforms, where the impact can be extensive.
- Card-Not-Present (CNP) Fraud: Card-not-present fraud involves the use of stolen credit or debit card information to make transactions where the physical card is not required, such as online or over-the-phone purchases [48] [49]. This type of fraud exploits the lack of physical verification, relying on stolen card details obtained through various means such as data breaches or phishing. CNP fraud poses a significant challenge for merchants and financial institutions due to the difficulty of verifying the legitimacy of transactions.
- Identity Theft: Identity theft occurs when fraudsters use stolen personal information to open accounts, obtain credit, or commit other fraudulent activities under someone else's name [50]. This often involves the theft of personal details such as Social Security numbers, addresses, and financial information. The impact of identity theft can be severe, affecting an individual's credit rating and personal finances.
- Friendly Fraud: Friendly fraud, also known as charge-back fraud, involves a consumer making a legitimate purchase but later disputing the transaction to obtain a refund while keeping the goods or services [51]. This type of fraud exploits the chargeback system, designed to protect consumers from unauthorized transactions but can be misused to defraud merchants.

2) Emerging Fraud Techniques:

- Synthetic Identity Fraud: Synthetic identity fraud involves the creation of a fictitious identity using a combination of real and fake information. Fraudsters use this synthetic identity to open accounts, accumulate credit, and commit fraud before the deception is discovered [36] [46] [2]. This type of fraud is challenging to detect because the synthetic identity often appears legitimate to automated systems.
- Deepfake Technology: Deepfake technology, which uses artificial intelligence to create realistic but fake audio and video content, is increasingly being used for fraud. Fraudsters may use deepfakes to impersonate executives, conduct scams, or manipulate financial transactions by creating convincing but fraudulent communications [22] [31] [51]. The sophistication of deepfakes poses new challenges for detecting and preventing fraud.

The landscape of fraud in electronic transactions is dynamic and continually evolving. Understanding the various types of fraud, from traditional phishing to emerging techniques like synthetic identity fraud, is crucial for developing effective detection and prevention strategies. As fraud tactics advance, so must the methods to combat them, ensuring that both consumers and businesses remain protected in an increasingly digital financial world

E. Fraud Detection Technologies

Fraud detection technologies are critical for safeguarding electronic transactions against a variety of fraudulent activities. With the increasing sophistication of fraudsters, leveraging advanced technologies has become essential for identifying and mitigating fraud effectively. These technologies range from traditional rule-based systems to cutting-edge artificial intelligence (AI) and machine learning (ML) algorithms. This section explores the primary fraud detection technologies, their methodologies, and their applications in protecting electronic transactions.

1) Machine Learning and Artificial Intelligence:

- Supervised Learning: Supervised learning is a type of machine learning where models are trained on labeled datasets, meaning that the training data includes examples of both fraudulent and legitimate transactions. Algorithms such as logistic regression, decision trees, and support vector machines are commonly used in supervised learning [52] [53]. These models learn to distinguish between fraudulent and non-fraudulent transactions based on features such as transaction amount, frequency, and location. A credit card company might use supervised learning to develop a model that classifies transactions as either "fraudulent" or "non-fraudulent" based on historical data. The model is trained on past transaction records and then applied to new transactions to predict potential fraud (Brown & Green, 2022).
- Unsupervised Learning: Unsupervised learning involves analyzing unlabeled data to identify patterns and anomalies without prior knowledge of fraud examples. Techniques such as clustering and anomaly detection are used to identify unusual transaction patterns that may indicate fraudulent activity [54]. This approach is beneficial for detecting new or evolving fraud patterns that were not previously encountered. An unsupervised learning algorithm might cluster transactions into groups based on similar characteristics. Transactions outside these clusters or exhibiting unusual patterns are flagged for further investigation.
- Predictive Analytics: Predictive analytics uses historical data and statistical algorithms to forecast future fraud risk. Machine learning models can analyze past transaction data to predict the likelihood of fraud in future transactions [55]. This approach combines supervised and unsupervised learning elements to enhance detection accuracy. A predictive model might analyze transaction history to forecast the likelihood of fraud based on factors such as recent changes in spending behavior or location. This helps in proactively identifying high-risk transactions.
- Rule-Based Systems: Rule-based systems rely on predefined rules and thresholds to detect fraud. These systems are often based on heuristics or expert knowledge and are designed to flag transactions that meet certain criteria [56]. A rule-based system will flag transactions that exceed a specific amount or occur in a geographic location that deviates from a user’s normal behavior. A bank might implement a rule that flags any transaction over $1,000 that occurs outside of a customer’s usual geographic area. While rule-based systems are straightforward to implement, they can be less flexible and may miss sophisticated fraud schemes.
- Behavioral Analytics: Behavioral analytics focuses on monitoring and analyzing user behavior patterns to detect anomalies that may indicate fraud. This technology examines how users interact with systems and identifies deviations from their typical behavior [57]. Behavioral analytics can be integrated with other fraud detection technologies to provide a more comprehensive view of transaction risk. An online payment platform might analyze login times, transaction patterns, and device information to establish a user’s normal behavior profile. Transactions that deviate significantly from this profile, such as a sudden increase in transaction volume or an access attempt from an unusual device, are flagged for review.
- Integration of Technologies: Modern fraud detection systems often integrate multiple technologies to enhance detection capabilities. Combining machine learning, rule-based systems, and behavioral analytics allows for a more robust and adaptive approach to fraud detection (Wilson & Thompson, 2023). This integration helps address individual technologies' limitations and improve overall detection accuracy.

Example: A comprehensive fraud detection system might use machine learning algorithms to analyze transaction patterns, rule-based systems to enforce thresholds, and behavioral analytics to monitor user behavior. This multi-layered approach increases the likelihood of identifying both known and emerging fraud threats (Chen & Lee, 2024).

Despite advancements in fraud detection technologies, several challenges remain. Machine learning models can be vulnerable to biases in training data and may struggle with false positives. Rule-based systems may not adapt well to evolving fraud tactics, and behavioral analytics requires significant data to establish accurate user profiles (Smith & Chang, 2023). Addressing these challenges requires continuous improvement and adaptation of fraud detection systems.

Fraud detection technologies are essential for protecting electronic transactions from a variety of fraudulent activities. By leveraging machine learning, rule-based systems, and behavioral analytics, organizations can enhance their ability to detect and mitigate fraud. However, ongoing innovation and adaptation are necessary to address emerging threats and ensure the effectiveness of fraud detection systems.

III. METHODOLOGY

The primary goal of this research is to develop and compare the effectiveness of different fraud detection methods using a real-world dataset. The focus is on evaluating the performance of individual techniques, such as rule-based systems, machine learning algorithms, and behavioral analytics, and then integrating these methods to create a comprehensive fraud detection system. A comprehensive description of the method adopted in this work is enumerated below.

1) Methods and Models:

- Rule-Based System: A simple rule-based approach was implemented, where transactions were flagged based on predefined thresholds and conditions. This method aimed to capture obvious fraud patterns.

$$\hat{y} = \begin{cases} 1, & \text{if } f(x) \geq \theta \text{ or } g(x) \text{ satisfies condition } C \\ 0, & otherwise \end{cases}$$

where:

– $\hat{y}$ is the flag for the transaction (1 for fraud, 0 for non-fraud).

– $f(x)$ represents a function applied to the transaction features x (e.g., amount, frequency).

– θ is a predefined threshold.

– $g(x)$ represents another function or condition applied to the features.

– C represents a predefined condition for flagging transactions.

- Machine Learning Model: Three machine learning algorithms was used namely Random Forest classifier, Gradient Boosting and Logistic Regression. The model was trained on the labeled dataset to learn patterns associated with fraudulent transactions. This approach was expected to perform better than the rule-based system by capturing complex patterns.

Random Forest

The prediction yˆ from a Random Forest for a sample x is given by:

$$\hat{y} = \frac{1}{M}\sum_{m=1}^{M} h_m(x)$$

where M is the number of trees in the forest, and $h_m(x)$ is the prediction from the m-th tree.

Gradient Boosting

The prediction yˆ from Gradient Boosting for a sample x is given by:

$$\hat{y} = F_o(x) + \sum_{m=1}^{M} \gamma_m h_m(x)$$

where $F_0(x)$ is the initial model, γ_m are the weights for the m-th tree, $h_m(x)$ are the weak learners (e.g., trees), and M is the number of boosting iterations.

Logistic Regression

The probability $P(Y = 1|x)$ of the positive class in Logistic Regression is given by:

$$P(Y = 1|x) = \frac{1}{1 + e^{-(\beta_o + \beta^T x)}}$$

where β_0 is the intercept, β is the vector of coefficients, and x is the feature vector. The decision boundary is typically set at 0.5, so if $P(Y = 1|x) \geq 0.5$, the prediction is class 1; otherwise, it is class 0.

- Behavioral Analytics (Anomaly Detection): An Isolation Forest was employed to detect anomalies in user behavior. This method aimed to identify unusual patterns that may indicate fraud, even if they do not match known fraud patterns.

Isolation Forest Anomaly Score

The anomaly score $s(x)$ for a sample x using Isolation Forest is computed based on the path length of x in the trees of the forest. If $E(x)$ is the average path length of x across all trees, the anomaly score can be calculated as:

$$s(x) = 2^{\frac{E(x)}{c(n)}}$$

where:

– $E(x)$ is the average path length of x across all trees.

– $c(n)$ is a normalization factor for the path length, which depends on the number of samples n in the forest.

The normalization factor $c(n)$ is defined as:

$$c(n) = 2 \cdot (\log_2(n) + \gamma)$$

where γ is an additional constant to account for small sample sizes.

Isolation Forest Construction

Isolation Forest builds an ensemble of Isolation Trees (iTrees). Each Isolation Tree is constructed by randomly selecting a feature and then randomly selecting a split value between the minimum and maximum values of that feature. This process is repeated recursively to isolate observations.

The probability of anomaly $p(x)$ for a sample x is determined by:

$$p(x) = \frac{1}{M}\sum_{m=1}^{M} score_m(x)$$

where:

– M is the number of isolation trees in the forest.

– $\text{score}_m(x)$ is the anomaly score for x computed by the m-th isolation tree.

The anomaly score is higher for points that are more easily isolated (i.e., have shorter path lengths), indicating a higher likelihood of being anomalies.

- Integrated Method: The predictions from the rule-based system, machine learning model, and behavioral analytics were combined using logical OR to create an integrated approach. The goal was to leverage the strengths of each method to improve overall fraud detection. To combine the predictions from the rule-based system, machine learning model, and behavioral analytics using a logical OR to create an integrated approach, the integrated prediction $y\hat{}_{\text{integrated}}$ can be expressed as:

$$\hat{y}_{integrated} = R(x) \vee M(x) \vee B(x)$$

where:

- $R(x)$ represents the prediction from the rule-based system,
- $M(x)$ represents the prediction from the machine learning model,
- $B(x)$ represents the prediction from behavioral analytics.

In this expression, $\vee$ denotes the logical OR operation. The predictions $R(x)$, $M(x)$, and $B(x)$ are binary values where 1 indicates a positive prediction (e.g., fraud detected) and 0 indicates a negative prediction. The integrated prediction $y\hat{}_{\text{integrated}}$ will be 1 if any of the individual predictions indicate a positive outcome.

2) Evaluation Metrics:

- Accuracy: Measures the proportion of correctly classified transactions (both fraud and non-fraud) out of the total transactions. It is used to gauge the overall effectiveness of the model.

The accuracy of a model is defined as:

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

- Precision: The proportion of true fraud cases among all transactions flagged as fraud. High precision indicates that the method is good at minimizing false positives. The mathematical expression for precision is given by:

$$Precision = \frac{TP}{TP + FP}$$

where TP stands for True Positives and FP stands for False Positives.

- Recall: The proportion of actual fraud cases that were correctly identified. High recall indicates that the method is effective at catching fraudulent transactions.

$$Recall = \frac{TP}{TP + FN}$$

- F1-Score: The harmonic mean of precision and recall, providing a single metric that balances both aspects. It is particularly useful when the class distribution is imbalanced, as it was in this research. The F1 score is given by:

$$F1 = \frac{2 \times Precision\ \times Recall}{Precision + Recall}$$

- Root Mean Squared Error (RMSE): It measures the average difference between values predicted by a model and the actual values. It provides an estimation of how well the model is able to predict the target value (accuracy). The lower the value of the Root Mean Squared Error, the better the model is. The Root Mean Squared Error (RMSE) is given by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

where:

- n is the number of observations,
- y_i is the actual value,
- $\hat{y}$ is the predicted value.

- Least Squared Error (LSE): It is a commonly used metric to evaluate the performance of regression models, where the goal is to measure how well the model's predictions match the actual data.

The Least Squares Error (LSE) is given by:

$$LSE = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

where:

- y_i is the actual value,
- $\hat{y}_i$ is the predicted value, and – n is the number of observations.

3) Experimental Setup:

- Dataset Description The dataset used in this research is a simulated financial transaction dataset containing both legitimate and fraudulent transactions. The dataset includes features such as:

- ‘type‘: The type of transaction (e.g., transfer, cash out).
- ‘amount‘: The amount of the transaction.
- ‘oldbalanceOrg‘: The original balance before the transaction.
- ‘newbalanceOrig‘: The balance after the transaction.
- ‘isFraud‘: A binary label indicating whether the transaction is fraudulent or not.

- Data Preprocessing: - Feature Engineering: New features were created to enhance the detection process, including the difference between the original balance and the transaction amount, the ratio of the transaction amount to the original balance, and the transaction count per user. - Data Splitting: The dataset was split into training and testing sets to allow for model evaluation and validation.

4) Experimental Procedure:

- Model Training: The Random Forest model was trained on the training set, which contained both fraudulent and non-fraudulent transactions. The training process involved learning patterns and associations in the data that could differentiate between the two classes.

Method	Rule-Based	Machine Learning	Behavioral	Integrated
Accuracy	0.116338	0.999992	0.98878	0.116030
Precision	0.001378	0.997942	0.002151	0.001441
Recall	0.9560574	0.995893	0.016837	1.0
F1-Score	0.002752	0.996916	0.003816	0.002877

Table I: Model Performance Comparison

- Anomaly Detection: The Isolation Forest model was trained to identify transactions that deviate significantly from normal user behavior. This approach is unsupervised and does not require labeled data.
- Prediction and Integration: Each method was used to predict fraud on the test set. The predictions from the individual methods were then integrated using a logical OR operation to assess whether combining them could improve detection performance.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The experimental results reveal distinct performance differences across the evaluated methods in detecting fraud in third party transactions. Table I presents the results.

A. Rule-Based System

- Accuracy: Very low at 11.63% indicating that the rule-based method incorrectly labels most transactions.
- Precision:Extremely low at 0.14%, meaning that very few flagged transactions are actually fraudulent.
- Recall: High recall at 95.61% shows that the method catches almost all fraudulent transactions but at the cost of flagging many legitimate transactions as fraudulent.
- F1-Score:Low F1-Score at 0.27%, indicating an imbalance between precision and recall, heavily skewed towards recall.
- Conclusion: The rule-based system is overly simplistic and flags too many transactions, resulting in a very high false positive rate. This method is not effective for fraud detection in this context.

B. Machine Learning Model

- Accuracy: Extremely high accuracy at 99.999%, indicating the model correctly classifies almost all transactions.
- Precision:Very high precision at 99.79%, means that nearly all transactions flagged as fraudulent are indeed fraud.
- Recall:High recall of 99.59%, shows that the model catches almost all fraudulent transactions.
- F1-Score: The F1-score of 99.69%, is also very high, indicating a good balance between precision and recall.
- Conclusion:The machine learning model performs exceptionally well as shown in Figure 1 , making it the most effective method for detecting fraud in this dataset.

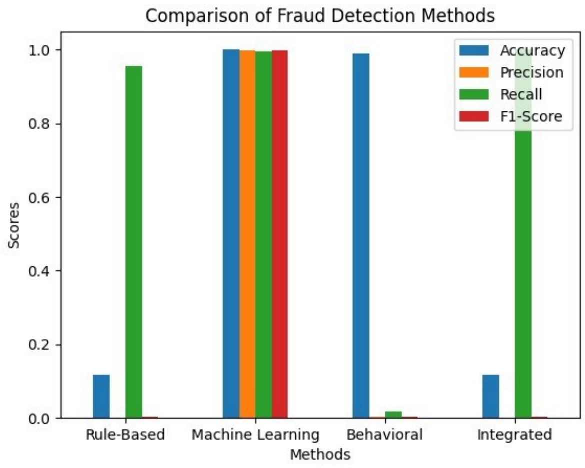

Figure 1: Comparison of Fraud Detection Methods

C. Behavioral Analytics (Isolation Forest)

- Accuracy: High accuracy of 98.88%, but not as high as the machine learning model.
- Precision:Very low precision of 0.21%, indicating that most flagged transactions are not fraudulent.
- Recall:Very low recall of 1.68 which means that only a small fraction of fraudulent transactions are detected.
- F1-Score:Very low F1-score of 0.38%, indicating poor performance overall.

  Behavioral analytics, as implemented here, does not perform well. The method has a low precision and recall, indicating it misses many fraudulent transactions and incorrectly flags many legitimate transactions.

D. Integrated Method

- Accuracy:Very low at 11.60% , similar to the rulebased system.
- Precision:Extremely low precision of 0.14%, meaning that almost all flagged transactions are not actually fraudulent.
- Recall:The recall is perfect 100%, meaning all fraudulent transactions are flagged, but this comes at the cost of an overwhelming number of false positives.
- F1-Score:Low F1-Score of 0.28%, indicating a significant imbalance between precision and recall, skewed towards recall.

The integrated method suffers from the same issues as the rule-based system, where an overly broad approach leads to many false positives. The integration of the methods, as implemented, does not improve the overall performance.

V. CONCLUSION

The research findings indicate that different methods used in fraud detection exhibit varying levels of effectiveness, with the machine learning approach standing out as the most reliable. Specifically, the Random Forest classifier demonstrated the highest performance across all evaluation metrics, including accuracy, precision, recall, and F1-score. This makes it the most effective method for detecting fraudulent activities while minimizing false positives.

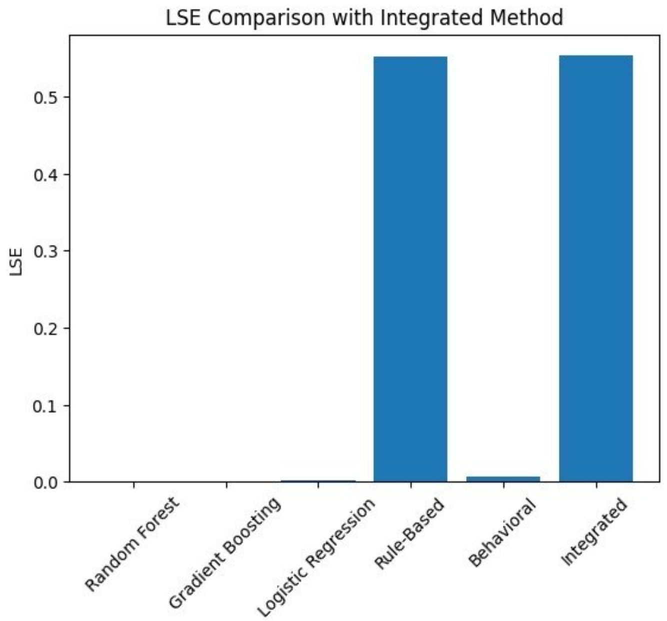

Figure 2: Least Squared Error

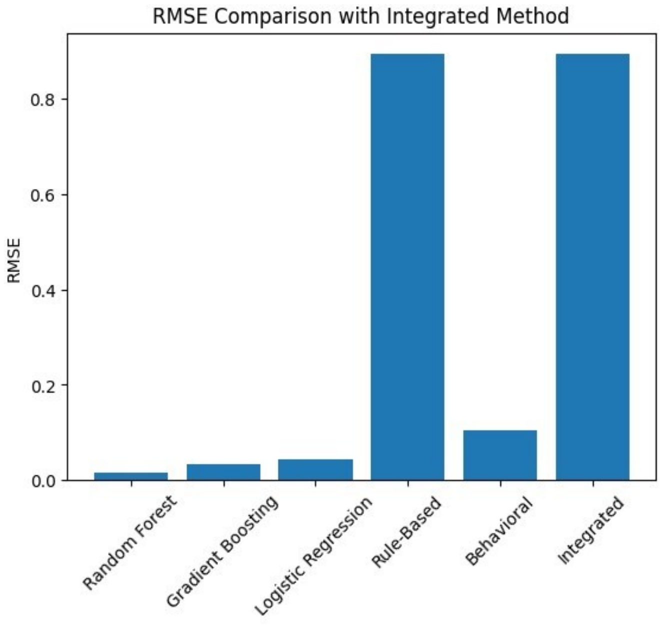

Figure 3: Root Mean Square Error

Conversely, while achieving high recall, the rule-based system struggled with precision, leading to a significant number of false positives. This indicates that while it can detect potential fraud, it lacks the specificity needed to accurately filter out legitimate transactions.

The behavioral analytics approach showed the weakest performance, with low precision and recall, suggesting that it was not well-suited for the context of this study. This method's limitations in accurately identifying fraud highlight the challenges of relying solely on behavioral patterns.

The integrated method, which combined multiple approaches, did not improve upon the performance of the machine learning model alone. Instead, it mirrored some of the issues seen with the rule-based system, particularly in generating false positives. This outcome suggests that simply combining methods is not enough; a more nuanced approach to integration is required.

In summary, the research underscores the superiority of machine learning models, particularly the Random Forest classifier, in fraud detection. While traditional methods like rule-based systems and behavioral analytics can offer some value, they are not as effective in isolation. Future research should focus on refining integrated approaches to leverage the strengths of each method while mitigating their weaknesses, ultimately leading to more accurate and reliable fraud detection systems.

REFERENCES

[1] A. S. George, "Finance 4.0: The transformation of financial services in the digital age," 2024.

[2] A. G. Carstens and N. Nilekani, Finternet: the financial system for the future. Bank for International Settlements, Monetary and Economic Department, 2024.

[3] K. Nidhi Varghese, D. M. V. Thangam, and M. A. Shalet, "Banking evolution: Unveiling the technological revolution through ict integration," Journal of Research Administration, vol. 5, no. 2, pp. 1680–1688, 2023.

[4] C. Nicolini, "Mobile payments: Emergence of dominant design in layered architectures," Ph.D. dissertation, Politecnico di Torino, 2023.

[5] P. Michalopoulos, O. Olowookere, N. Pocher, J. Sedlmeir, A. Veneris, and P. Puri, "Compliance design options for offline cbdcs: Balancing privacy and aml/cft," in 2024 IEEE International Conference on Blockchain and Cryptocurrency (ICBC), IEEE, 2024.

[6] G. Chodak, "The future of e-commerce," Springer Books, 2024.

[7] K. Patel, "Credit card analytics: a review of fraud detection and risk assessment techniques," International Journal of Computer Trends and Technology, vol. 71, no. 10, pp. 69–79, 2023.

[8] A. Cherif, A. Badhib, H. Ammar, S. Alshehri, M. Kalkatawi, and A. Imine, "Credit card fraud detection in the era of disruptive technologies: A systematic review," Journal of King Saud University-Computer and Information Sciences, vol. 35, no. 1, pp. 145–174, 2023.

[9] R. E. Daraojimba, O. A. Farayola, F. O. Olatoye, N. Mhlongo, and T. T. Oke, "Forensic accounting in the digital age: a us perspective: scrutinizing methods and challenges in digital financial fraud prevention," Finance & Accounting Research Journal, vol. 5, no. 11, pp. 342–360, 2023.

[10] A. C. Dewi, E. I. H. Ujianto, and R. Rianto, “Electronic payment threats and security: A systematic literature review,” Jurnal Nasional Pendidikan Teknik Informatika: JANAPATI, vol. 13, no. 2, pp. 301–315, 2024.

[11] B. Mohanty, S. Mishra et al., “Role of artificial intelligence in financial fraud detection,” Academy of Marketing Studies Journal, vol. 27, no. S4, 2023.

[12] A. C. Tambe Ebot, M. Siponen, and V. Topalli, “Towards a cybercontextual transmission model for online scamming,” European Journal of Information Systems, vol. 33, no. 4, pp. 571–596, 2024.

[13] G. Sarkar and S. K. Shukla, “Behavioral analysis of cybercrime: Paving the way for effective policing strategies,” Journal of Economic Criminology, p. 100034, 2023.

[14] P. Zanke, “Ai-driven fraud detection systems: a comparative study across banking, insurance, and healthcare,” Advances in Deep Learning Techniques, vol. 3, no. 2, pp. 1–22, 2023.

[15] F. T. Johora, R. Hasan, S. F. Farabi, J. Akter, and M. A. Al Mahmud, “Ai-powered fraud detection in banking: Safeguarding financial transactions,” The American Journal of Management and Economics Innovations, vol. 6, no. 06, pp. 8–22, 2024.

[16] A. V. Tulsi and D. D. Patil, “Prevention service for fraudulent and non fraudulent payments using online payment,” International Journal Of Engineering And Management Research, vol. 13, no. 6, pp. 119–140, 2023.

[17] T. E. Ede, “E-business management practices on the performance of small scale entrepreneurs (sse) in ebonyi state,” EBSU Journal of Social Sciences and Humanities, vol. 13, no. 3, 2023.

[18] G. J. Ochieng’Oyugi and M. Kamaara, “E-procurement practices and procurement performance in kenya’s state enterprises,” International Journal of Management and Business Research, vol. 5, no. 2, pp. 383–395, 2023.

[19] R. Sharma, S. Srivastva, and S. Fatima, “E-commerce and digital transformation: Trends, challenges, and implications,” International Journal for Multidisciplinary Research (IJFMR), vol. 5, no. 5, 2023.

[20] L. Kasowaki and I. Faris, “Elevating transactions: the role of internet banking in revolutionizing e-commerce experiences,” EasyChair, Tech. Rep., 2024.

[21] H. Taherdoost, “Billing and payment systems,” in E-Business Essentials: Building a Successful Online Enterprise. Springer, 2023, pp. 137–162.

[22] D. M. Aloun, “Commercial applications of electronic currencies,” International Journal, vol. 5, no. 10, pp. 2126–2137, 2024.

[23] B. Radenkovic, M. Despotovi´ c-Zraki´ c, and A. Labus, “Digital payment´ systems: state and perspectives,” in Digital Transformation of the Financial Industry: Approaches and Applications. Springer, 2023, pp. 203–216.

[24] L.-H. Lin, F.-C. Lin, C.-K. Lien, T.-C. Yang, Y.-K. Chuang, and Y.-W. Hsu, “Electronic payment behaviors of consumers under digital transformation in finance—a case study of third-party payments,” Journal of Risk and Financial Management, vol. 16, no. 8, p. 346, 2023.

[25] I. Niankara and R. I. Traoret, “The digital payment-financial inclusion nexus and payment system innovation within the global open economy during the covid-19 pandemic,” Journal of Open Innovation: Technology, Market, and Complexity, vol. 9, no. 4, p. 100173, 2023.

[26] M. R. N. A. Hendrawan, S. A. Marits, and S. Herman, “Development of digital payment systems in indonesia,” Jurnal Ilmiah Manajemen Kesatuan, vol. 11, no. 3, pp. 1335–1344, 2023.

[27] M. Younus, A. Nurmandi, W. Suardi, and H. Gul, “Government initiative to promote cashless transaction through innovative payment solutions to provide ease and safety to pay online,” Formosa Journal of Applied Sciences, vol. 2, no. 9, pp. 2141–2154, 2023.

[28] B. Vinod, “The impact of emerging technologies on intermediaries,” in Mastering the Travel Intermediaries: Origins and Future of Global Distribution Systems, Travel Management Companies, and Online Travel Agencies. Springer, 2024, pp. 363–394.

[29] L. Albshaier, S. Almarri, and M. Hafizur Rahman, “A review of blockchain’s role in e-commerce transactions: Open challenges, and future research directions,” Computers, vol. 13, no. 1, p. 27, 2024.

[30] A. Faccia, “National payment switches and the power of cognitive computing against fintech fraud,” Big Data and Cognitive Computing, vol. 7, no. 2, p. 76, 2023.

[31] O. Oriji, M. A. Shonibare, R. E. Daraojimba, O. Abitoye, and C. Daraojimba, “Financial technology evolution in africa: a comprehensive review of legal frameworks and implications for ai-driven financial services,” International Journal of Management & Entrepreneurship Research, vol. 5, no. 12, pp. 929–951, 2023.

[32] H. Zhang, “Analysis of internet third-party payment based on alipay mobile payment business,” Frontiers in Business, Economics and Management, vol. 11, no. 2, pp. 212–219, 2023.

[33] H. Xia, Y. Gao, and J. Z. Zhang, “Understanding the adoption context of china’s digital currency electronic payment,” Financial Innovation, vol. 9, no. 1, p. 63, 2023.

[34] Y. Xu, A. Ghose, and B. Xiao, “Mobile payment adoption: An empirical investigation of alipay,” Information Systems Research, vol. 35, no. 2, pp. 807–828, 2024.

[35] S. W. Koh, A. Shamsudin, T. Ong, A. Nurhazli, F. Muhamad, and Y. F. Yasin, “Demographic and behavioral profiling of e-wallet users: A comparative analysis of e-wallet platforms,” JOURNAL INFORMATION AND TECHNOLOGY MANAGEMENT (JISTM), vol. 9, no. 35, 2024.

[36] O. B. Adeoye, W. A. Addy, O. Odeyemi, C. C. Okoye, O. C. Ofodile, A. T. Oyewole, and Y. J. Ololade, “Fintech, taxation, and regulatory compliance: navigating the new financial landscape,” Finance & Accounting Research Journal, vol. 6, no. 3, pp. 320–330, 2024.

[37] K. Mullangi, “Innovations in payment processing: Integrating accelerated testing for enhanced security,” American Digits: Journal of Computing and Digital Technologies, vol. 1, no. 1, pp. 18–32, 2023.

[38] O. Efijemue, C. Obunadike, E. Taiwo, S. Kizor, S. Olisah, C. Odooh, and I. Ejimofor, “Cybersecurity strategies for safeguarding customers data and preventing financial fraud in the united states financial sectors,” International Journal of Soft Computing, vol. 14, no. 3, pp. 10–5121, 2023.

[39] I. Ahmad, S. Khan, and S. Iqbal, “Guardians of the vault: unmasking online threats and fortifying e-banking security, a systematic review,” Journal of Financial Crime, 2024.

[40] S. Tatineni and A. Mustyala, “Enhancing financial security: Data science’s role in risk management and fraud detection,” ESP International Journal of Advancements in Computational Technology (ESP-IJACT), vol. 2, no. 2, pp. 94–105, 2024.

[41] A. E. Maseko, “Remedies to reduce user susceptibility to phishing attacks,” Ph.D. dissertation, University of the Western Cape, 2023.

[42] R. Goenka, M. Chawla, and N. Tiwari, “A comprehensive survey of phishing: Mediums, intended targets, attack and defence techniques and a novel taxonomy,” International Journal of Information Security, vol. 23, no. 2, pp. 819–848, 2024.

[43] D. Hummer and D. J. Rebovich, “Identity theft and financial loss,” in Handbook on Crime and Technology. Edward Elgar Publishing, 2023, pp. 38–53.

[44] R. K. Abdelhamid and M. Maqableh, “The power of persuasion: Exploring social engineering in the digital age,” in Current and Future Trends on Intelligent Technology Adoption: Volume 2. Springer, 2024, pp. 307–330.

[45] A. Bobokulov, “The impact of social engineering on cybercrime: Psychological manipulation and prevention methods,” International Journal of Cyber Law, vol. 1, no. 5, 2023.

[46] A. Bansal, T. Khosla, and V. K. Saini, “Security challenges and various methods for increasing security in e-commerce applications,” International Journal for Research in Applied Science and Engineering Technology, 2023.

[47] D. Senecal, The Reign of Botnets: Defending Against Abuses, Bots and Fraud on the Internet. John Wiley & Sons, 2024.

[48] M. Bojilov, “Methods for assisting in detection of synthetic identity fraud in credit applications in financial institutions,” Ph.D. dissertation, CQUniversity, 2023.

[49] A. Husejinovic, J. Kevri´ c, N. Durmi´ c, and S. Juki´ c, “Credit card fraud´ payments detection using machine learning classifiers on imbalanced data set optimized by feature selection,” in International Symposium on Innovative and Interdisciplinary Applications of Advanced Technologies. Springer, 2023, pp. 233–250.

[50] A. R. Ilzan, R. F. B. Oktaviani, F. M. Yusuf, D. J. Wegman, N. Y. Imtiyaz et al., “Understanding the phenomenon and risks of identity theft and fraud on social media,” Asia Pacific Journal of Information System and Digital Transformation, vol. 1, no. 01, pp. 23–32, 2023.

[51] M. S. Seshamamba, “Consumer fraud and deceptive marketing techniques: An analysis of legal remedies,” Issue 2 Indian JL & Legal Rsch., vol. 5, p. 1, 2023.

[52] J. Soni, P. Gangwani, S. Sirigineedi, S. Joshi, N. Prabakar, H. Upadhyay, and S. A. Kulkarni, "Deep learning approach for detection of fraudulent credit card transactions," in Artificial Intelligence in Cyber Security: Theories and Applications. Springer, 2023, pp. 125–138.

[53] R. Saxena, D. Arora, and V. Nagar, "Classifying transactional addresses using supervised learning approaches over ethereum blockchain," Procedia Computer Science, vol. 218, pp. 2018–2025, 2023.

[54] Z. Huang, H. Zheng, C. Li, and C. Che, "Application of machine learning-based k-means clustering for financial fraud detection," Academic Journal of Science and Technology, vol. 10, no. 1, pp. 33–39, 2024.

[55] M. E. Lokanan, "Predicting mobile money transaction fraud using machine learning algorithms," Applied AI Letters, vol. 4, no. 2, p. e85, 2023.

[56] O. S. Adebayo, T. A. Favour-Bethy, O. Otasowie, and O. A. Okunola, "Comparative review of credit card fraud detection using machine learning and concept drift techniques," Int. J. Comput. Sci. Mob. Comput, vol. 12, pp. 24–48, 2023.

[57] S. O. Olabanji, Y. Marquis, C. S. Adigwe, S. A. Ajayi, T. O. Oladoyinbo, and O. O. Olaniyi, "Ai-driven cloud security: Examining the impact of user behavior analysis on threat detection," Asian Journal of Research in Computer Science, vol. 17, no. 3, pp. 57–74, 2024.