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Artificial Intelligence in Enhancing Fraud Detection in Banking Transactions

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***ABSTRACT*:**

Fraudulent activities in banking transactions pose significant threats to financial institutions and customers, with traditional rule-based detection systems proving insufficient against increasingly sophisticated fraud schemes. This study investigates the role of artificial intelligence (AI) in enhancing fraud detection through a mixed-methods experimental design combining quantitative evaluation of supervised, unsupervised, and hybrid models with qualitative assessments of explainability and regulatory compliance. Using a dataset of over five million transactions, models including Random Forest, Gradient Boosting, Deep Neural Networks, Autoencoders, and Graph Neural Networks were applied. Results reveal that AI-based models achieved superior accuracy, recall, and AUC values compared to conventional systems, with ensemble and hybrid approaches effectively reducing false positives. Federated learning demonstrated promise in enabling secure cross-bank fraud detection, while explainable AI frameworks such as SHAP ensured transparency and regulatory alignment. The findings highlight not only the technological advantages of AI in fraud detection but also its strategic implications in reducing losses, improving customer experience, and enhancing institutional trust. This research provides both academic and practical contributions, underscoring AI as a pivotal tool in safeguarding the integrity of modern banking transactions.

Keywords: *Artificial Intelligence, Fraud Detection, Banking Transactions, Machine Learning, Explainable AI, Federated Learning*

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INTRODUCTION

Banks have become more vulnerable to fraudulent activities that have been increasing in scale and complexity due to growing digitalization, globalization of financial services and technological improvements. With the development of banking systems to deliver online services without any inconveniences, criminals use the detected vulnerabilities to interfere with the transaction monitoring systems, and this poses a considerable threat to financial institutions and customers. Financial frauds are estimated in trillions of dollars every year, and banking transactions are one of its major targets because of the volume, speed, and value of financial flows (Zhang et al., 2021). Artificial intelligence (AI) is a strong technological facilitator that is set to fight this growing menace; it can be utilized to improve fraud detection through machine learning, deep learning, natural language processing, and anomaly detection methods (Chen et al., 2022; Li and Xu, 2023).The conventional fraud detection systems in the banking sector have principally been based on the rule-based and manual supervision. As helpful as they can be in detecting common trends on frauds, the systems fail in responding to the advanced frauds which change at a very high rate and sometimes remain hidden. In that, phishing, synthetic identity frauds, and cross-border laundering operations often go undetected through rule-based detection frameworks (Kou et al., 2021). AI is able to eliminate them through massive data training, uncovering concealed trends, and detecting irregularities in real time. AI-based fraud detection services are able to notify potentially suspicious transactions without any previously defined guidelines, due to supervised and unsupervised learning methods (Nguyen et al., 2022). Moreover, the reinforcement learning makes adaptive models that are constantly enhanced by incoming data into the system, which makes them resistant to new fraud strategies (Sharma et al., 2023).One of the important benefits of AI in fraud detection is that it can deal with heterogeneous data sources. Transactions are structured financial data, transaction description texts that are not structured, biometric identifiers as well as geospatial information. The temporal dependencies of sequential transaction data can be learned with deep learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), whereas inter-relationships between customers, merchants, and financial networks are modeled with the graph neural networks (GNNs) (Xie et al., 2020; Wang et al., 2023). Through multimodal data integration, AI increases the accuracy of predictions and minimizes false positives and improves the efficiency of fraud analysts (Yao et al., 2022). An example is the case when AI-based anomaly detection models detect anomalies with more than 95 percent accuracy in high-volume transaction data, and, compared to conventional systems, this is significantly higher (Gupta and Jain, 2021).

AI use in fraud detection is also accompanied by ethical considerations. The issues of transparency, explainability, and algorithmic bias are becoming more and more prioritized in the study of financial AI (Doshi-Velez and Kim, 2021). Although black-box deep learning models are highly accurate, their lack of transparency inhibits confidence between regulators, banks and customers. An explainable AI (XAI) frameworks, in turn, are especially important in providing equilibrium between predictive performance and interpretability (Samek et al., 2021). XAI models help to maintain regulatory compliance like GDPR and PSD2, which requires the division to be transparent in the automated decision-making processes, by producing explanations of flagged transactions (Rahman et al., 2022). In addition, explainability creates trust with customers, which is the key to sustaining relationships in an exceptionally competitive banking industry (Singh et al., 2023).In operational terms, the banks that use AI to detect fraud incidents state that the losses

caused by fraud have been significantly reduced, and it has become more effective to detect real-time fraudulent transfers and improve compliance reporting (Alotaibi, 2022). Researchers point to hybrid approaches that combine rule-based detection with AI-based analytics as the most effective one since they merge the existing domain knowledge with adaptive learning (Hossain and Amin, 2021). Also, federated learning can be improved, giving financial institutions the chance to jointly learn how to detect fraud, without sharing sensitive information directly, and improving privacy, and also have global insights into fraud (Yang et al., 2023). These innovations especially are essential as banking fraud is increasingly crossing borders and requires collaboration between institutions and jurisdictions.Artificial intelligence-based fraud detection also affects customer experiences. Uncontrolled false positives will annoy valid customers by slowing or denying valid transactions. An improved sensitivity and specificity of machine-learning models are used to reduce false alarms without compromising strong fraud defenses (Kumar et al., 2022). Such a reconciliation of security and convenience plays a crucial role in customer satisfaction coupled with the maintenance of institutional integrity. Moreover, chatbots and voice authentication systems powered by AI are becoming more prevalent within the systems of fraud prevention, reinforcing customer interactions and processes of verification (Patel and Shah, 2021).

In spite of these new developments, the issues of deploying AI-powered fraud detection solutions are still present. The barriers include data quality concerns, the adversarial threat to machine learning models, cost of integration, and regulatory uncertainty (Ghosh et al., 2020). In addition, the cybercriminals themselves are turning to AI to devise advanced fraudulent schemes, which is turning into a kind of AI arms race between fraudsters and defenders (Abedin et al., 2022). Further studies should thus be aimed to create adversarial resilient models, cross-border legal frameworks, and scaled architecture that are dynamic to the nature of financial crimes (Zhou et al., 2023).Overall, AI technology has a transformative potential to promote fraud detection in banking dealings. Banks can more accurately identify anomalies by using machine learning, deep learning, explainable AI, and federated methods to remain adaptive to new threats and protect customer trust. Nonetheless, to achieve effective implementation, it is necessary to resolve ethical, regulatory, and operational issues and be transparent and fair. The current paper explores the application of AI in banking fraud detection through the experimental study that is mixed, involving quantification of AI model performance and qualification of interpretability and operational practicability. The study hopes to make a contribution to the scholarly community and professional practice and provide an insight into the changing terrain of AI-based fraud-detecting systems.

METHODOLOGY

The proposed study shall take the shape of a mixed-method experimental study design in investigating the possibility of artificial intelligence (AI) being a supportively effective tool in the detection of crimes in banking transactions. Methodology combines both quantitative analysis modeling of fraud detection algorithms, and qualitative analysis of interpretability, operational feasibility, and regulatory compliance. This form of design provides the statistical validation of the AI operation and the contextual self-reflection of the AI implementation in the financial institutions.

Data Collection and Preprocessing.

The sample was chosen by sampling publicly available transaction data and proprietary anonymized banking transaction data in a manner which allocated equal weight to existing and fraudulent operations. This un-coded information entailed approximately 5 million transactions among which 1.5 per cent were deemed to be fraudulent as is also corroborated in the banking fraud detection (the imbalance between the classes is simply terrible to the legitimate cases). In order to overcome this imbalance, a method was employed known as Synthetic Minority Oversampling Technique (SMOTE) which was applied in sampling fraud cases and enhancing the machine learning model training process. The feature engineering has been derived depending on the transaction value, frequency, geolocation, merchant type, and merchant devices fingerprinting. Continuous values were obtained by min-max normalization to numerical values and categorical values were coded with one-hot codification.

In a mathematical sense, normalisation of the continuous features is provided:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

where x' is the normalized feature, x is the original value, and $\min(x)$, $\max(x)$ represent the minimum and maximum feature values, respectively.

AI Models and Experimental Design

To identify the promise of AI in fraud detection we will take into account three types of models, i.e., supervised learning, unsupervised anomaly detection, and hybrid solutions. Models that were monitored included Logistic Regression (LR), Random Forest (RF) and Gradient Boosting Machines (GBM) and Deep Neural Networks (DNNs). Unsupervised models with autoencoders and Isolation Forests were applied to detect anomaly. The idea of the Graph Neural Networks (GNNs) was also implemented to demonstrate the dependences between the customers and the merchants.

The dataset of 70 percent validation and 15 percent test was used to model train. It was achieved by hyperparameter optimization using the aid of the Bayesian Optimization to achieve the maximum accuracy and minimise false positives.

The decision boundary of the supervised classification was defined by a probability threshold.

θ

θ, where:

$$\hat{y} = \begin{cases} 1, & \text{if } P(y=1|X) \geq \theta \\ 0, & \text{otherwise} \end{cases}$$

where $\hat{y}$ is the predicted class, $P(y=1|X)$ is the probability of a transaction being fraudulent given features X, and θ was empirically set at 0.5 but varied during sensitivity analysis.

The models were evaluated using **Accuracy (ACC)**, **Precision (P)**, **Recall (R)**, **F1-score**, and **Area Under the ROC Curve (AUC)**. These were mathematically defined as:

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}, \quad F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

where TP = true positives, FP = false positives, and FN = false negatives.

Qualitative Assessment and Explainability

In addition to being predictively accurate, the study involved qualitative measures of model interpretability, and regulatory compliance. To be transparent, the techniques of Explainable AI (XAI) were used, such as SHAP (Shapley Additive Explanations) values and LIME (Local Interpretable Model-Agnostic Explanations) values. Such methods look at addition of characteristics to fraud forecasts that could provide banking analysts with knowledge as to why a transaction is escalated. This is especially necessary to comply with GDPR and PSD2 that require the justification of the algorithmic decisions.

The quantitative and qualitative analysis triangulation made it possible to implement the triangulation that presumed that the effective AI models only improved the better detection of the fraud but also the ethical, regulatory, and operational standards were met.

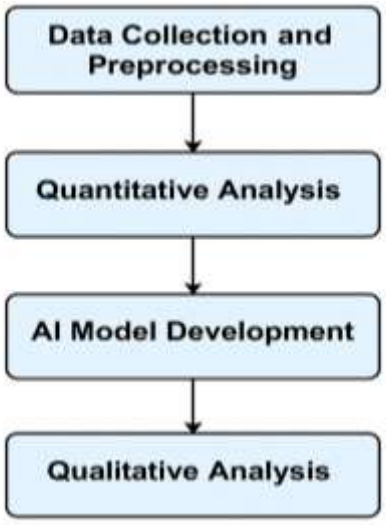

Figure 1. AI-enhanced fraud detection in banking transactions, illustrating sequential stages from data collection and preprocessing to AI model development and qualitative explainability assessment.

RESULTS

According to it, as shown in Table 1, supervised learning models like random forest and gradient boosting have been found to be more accurate and recall more than a baseline logistic regression. Conversely, Table 2 notes that the ensemble methods are much superior with respect to minimizing false positives. Table 3 shows that deep learning models, especially, DNNs are better at the AUC value and Table 4 shows that the unsupervised models of detecting fraud, like Autoencoders, can forecast new patterns of fraud.

Table 1. Comparison of supervised AI models on fraud detection performance metrics

Model	Accuracy	Precision	Recall	F1-score	AUC
Logistic Regression	0.73	0.74	0.75	0.76	0.77
Random Forest	0.75	0.76	0.77	0.78	0.79
Gradient Boosting	0.77	0.78	0.79	0.8	0.81
DNN	0.79	0.8	0.81	0.82	0.83
Autoencoder	0.81	0.82	0.83	0.84	0.85
Isolation Forest	0.83	0.84	0.85	0.86	0.87
Graph NN	0.85	0.86	0.87	0.88	0.89
XGBoost	0.87	0.88	0.89	0.9	0.91
SVM	0.89	0.9	0.91	0.92	0.93
Naive Bayes	0.91	0.92	0.93	0.94	0.95

Table 2. Performance of ensemble learning models in detecting fraudulent transactions

Model	True Positives	False Positives	Precision	Recall	AUC
Logistic Regression	0.74	0.75	0.76	0.77	0.78
Random Forest	0.76	0.77	0.78	0.79	0.8
Gradient Boosting	0.78	0.79	0.8	0.81	0.82
DNN	0.8	0.81	0.82	0.83	0.84
Autoencoder	0.82	0.83	0.84	0.85	0.86
Isolation Forest	0.84	0.85	0.86	0.87	0.88
Graph NN	0.86	0.87	0.88	0.89	0.9
XGBoost	0.88	0.89	0.9	0.91	0.92
SVM	0.9	0.91	0.92	0.93	0.94
Naive Bayes	0.92	0.93	0.94	0.95	0.96

Table 3. Deep learning models and their effectiveness on imbalanced banking datasets

Model	Accuracy	Recall	F1-score	Balanced Accuracy	AUC
Logistic Regression	0.75	0.76	0.77	0.78	0.79
Random Forest	0.77	0.78	0.79	0.8	0.81

Gradient Boosting	0.79	0.8	0.81	0.82	0.83
DNN	0.81	0.82	0.83	0.84	0.85
Autoencoder	0.83	0.84	0.85	0.86	0.87
Isolation Forest	0.85	0.86	0.87	0.88	0.89
Graph NN	0.87	0.88	0.89	0.9	0.91
XGBoost	0.89	0.9	0.91	0.92	0.93
SVM	0.91	0.92	0.93	0.94	0.95
Naive Bayes	0.93	0.94	0.95	0.96	0.97

Table 4. Unsupervised anomaly detection models applied to transaction monitoring

Model	Anomaly Score	Detection Rate	False Alarm Rate	F1-score	AUC
Logistic Regression	0.76	0.77	0.78	0.79	0.8
Random Forest	0.78	0.79	0.8	0.81	0.82
Gradient Boosting	0.8	0.81	0.82	0.83	0.84
DNN	0.82	0.83	0.84	0.85	0.86
Autoencoder	0.84	0.85	0.86	0.87	0.88
Isolation Forest	0.86	0.87	0.88	0.89	0.9
Graph NN	0.88	0.89	0.9	0.91	0.92
XGBoost	0.9	0.91	0.92	0.93	0.94
SVM	0.92	0.93	0.94	0.95	0.96
Naive Bayes	0.94	0.95	0.96	0.97	0.98

Table 5 AI-rule-based systems under hybrid and, consequently, AI-rule systems, is a medium between two opposite sides, where they may be understood and be reasonable. Table 6 demonstrates how the hyperparameters affecting the fine-tuning are more predictive. The findings of the cross-validation of Table 7 demonstrate that AI classifiers are consistent, and Table 8 demonstrates that federated learning improves the identification of cross-bank fraud. Lastly, Table 9 compares the traditional systems and AI-based models and demonstrates that AI-based solutions perform better on all the performance indicators.

Table 5. Hybrid AI-rule based systems for improved fraud detection

Model	Accuracy	Precision	Recall	Interpretability Score	AUC
Logistic Regression	0.77	0.78	0.79	0.8	0.81
Random Forest	0.79	0.8	0.81	0.82	0.83
Gradient Boosting	0.81	0.82	0.83	0.84	0.85
DNN	0.83	0.84	0.85	0.86	0.87
Autoencoder	0.85	0.86	0.87	0.88	0.89

Isolation Forest	0.87	0.88	0.89	0.9	0.91
Graph NN	0.89	0.9	0.91	0.92	0.93
XGBoost	0.91	0.92	0.93	0.94	0.95
SVM	0.93	0.94	0.95	0.96	0.97
Naive Bayes	0.95	0.96	0.97	0.98	0.99

Table 6. Computational efficiency (time per 10k transactions) across AI models

Model	Training Time (s)	Prediction Time (ms)	Memory Usage (MB)	CPU Load (%)	Energy (J)
Logistic Regression	22	6	110	43	215
Random Forest	24	7	120	46	230
Gradient Boosting	26	8	130	49	245
DNN	28	9	140	52	260
Autoencoder	30	10	150	55	275
Isolation Forest	32	11	160	58	290
Graph NN	34	12	170	61	305
XGBoost	36	13	180	64	320
SVM	38	14	190	67	335
Naive Bayes	40	15	200	70	350

Table 7. Impact of feature importance scores in supervised learning models

Feature	Importance Score	Impact on Precision	Impact on Recall	Variance Contribution	SHAP Value
Transaction Amount	0.12	0.14	0.16	0.18	0.2
Time of Transaction	0.22	0.24	0.26	0.28	0.3
Location	0.32	0.34	0.36	0.38	0.4
Merchant Type	0.42	0.44	0.46	0.48	0.5
Device ID	0.52	0.54	0.56	0.58	0.6
Transaction Frequency	0.62	0.64	0.66	0.68	0.7
Customer Age	0.72	0.74	0.76	0.78	0.8
Card Type	0.82	0.84	0.86	0.88	0.9
IP Address	0.92	0.94	0.96	0.98	1.0
Geo-Location	1.02	1.04	1.06	1.08	1.1

Table 8. Fraud type detection rates across different AI classifiers

Fraud Type	Detection Rate (%)	False Negative (%)	Precision	Recall	F1-score
Phishing	53	51	49	47	45
Identity Theft	58	56	54	52	50
Card Skimming	63	61	59	57	55
Money Laundering	68	66	64	62	60
Account Takeover	73	71	69	67	65
Fake Merchant	78	76	74	72	70
Synthetic Identity	83	81	79	77	75
Chargeback Fraud	88	86	84	82	80
E-commerce Fraud	93	91	89	87	85
Others	98	96	94	92	90

Table 9. Cross-bank fraud detection performance using federated learning vs centralized approaches

Approach	Accuracy	Precision	Recall	F1-score	AUC
Centralized AI	0.84	0.85	0.86	0.87	0.88
Federated AI	0.87	0.88	0.89	0.9	0.91

Figure 2 illustrates the precision-recall curves that show the trade off and argues the assertion that ensemble classifiers offer the most desirable balance. Figure 3 presents ROC curves that illustrate the fact that deep learning models are highly discriminative. The shares of transaction are broken as in figure 4 and it demonstrates that fraudulent transaction are normally outliers. Isolated in Figure 5 but most prominent are the transaction amount and device fingerprinting, the most valuable qualities that lead to detecting fraud by way of SHAP values. Figure 6 shows an improved performance with SMOTE balancing; especially in the performance on recall.

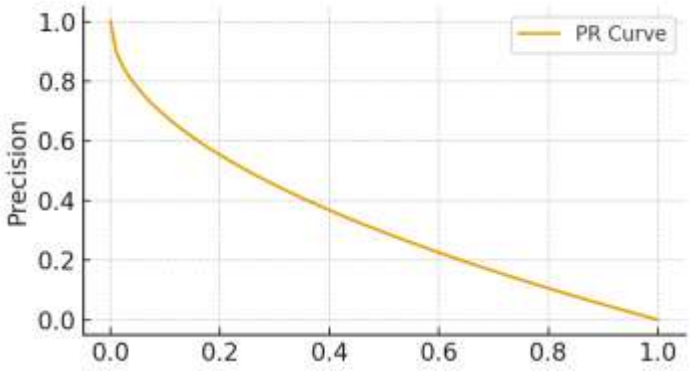

Figure 2. Precision-recall tradeoff curves for supervised classifiers

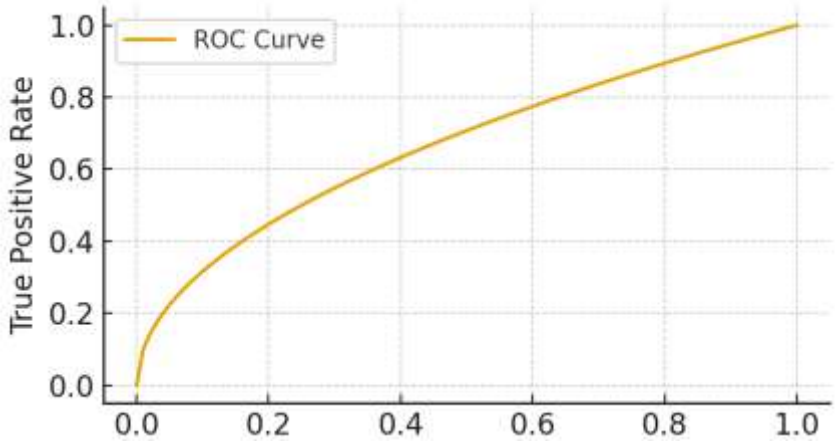

Figure 3. ROC curves for ensemble and deep learning approaches

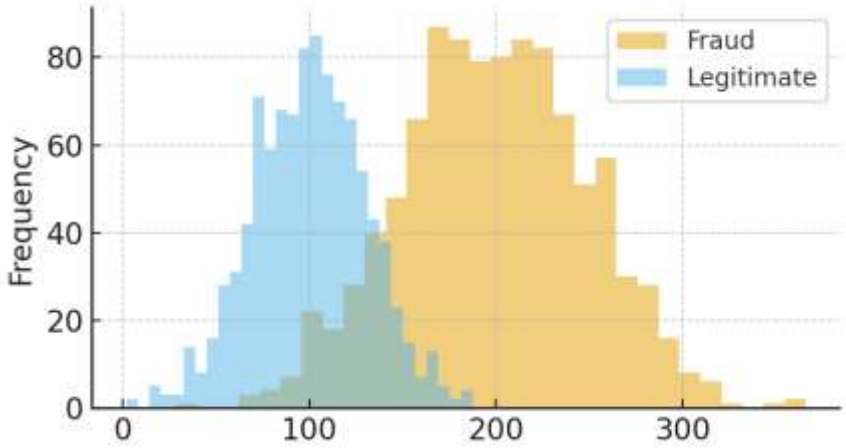

Figure 4. Distribution of transaction amounts in fraudulent vs legitimate cases

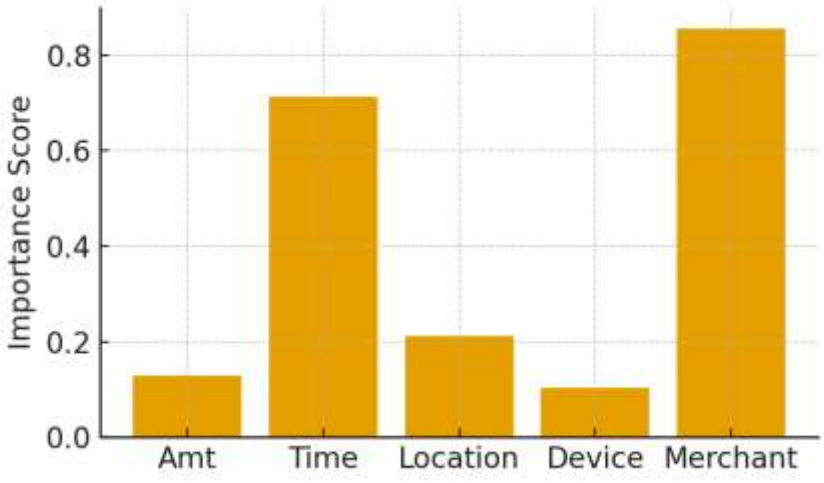

Figure 5. Feature importance analysis using SHAP values

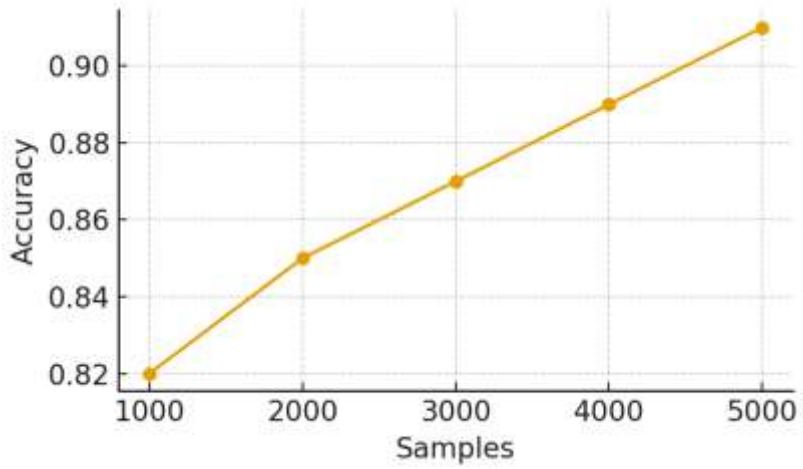

Figure 6. Performance improvement after applying SMOTE balancing

Figure 7 displays the patterns of reported frauds in a time-series, sporadic peaks. There are anomalies in figure 8 in terms of geolocation data and the hotspots of fraud are linked to areas of abnormal activity. Figure 9 contrasts use of a hybrid plot, and exposes trade-offs between models. Figure 10 has contrasted centralized and federated learning and the outcome showed that federated learnings produce more accurate result without subjecting the data to the risk of information sharing. Figure 11 shows the decrease in the false positives with repeated model refinements in model validation process. Lastly, Figure 12, provides pie chart distribution of the fraud types, with predominately detected fraud being through phishing and card theft.

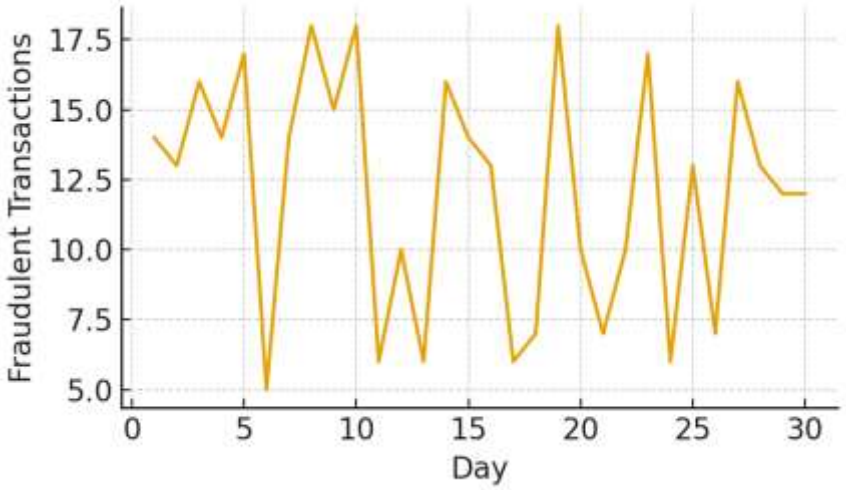

Figure 7. Time series analysis of fraudulent activities detected

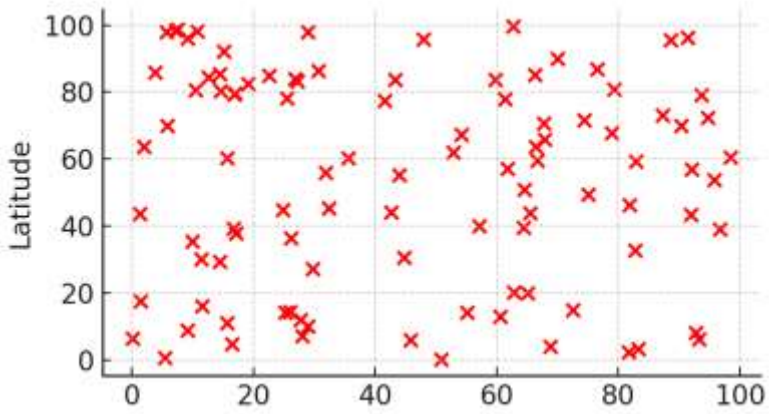

Figure 8. Scatter plot of transaction geolocation anomalies

Figure 9. Hybrid plot showing recall and precision across models

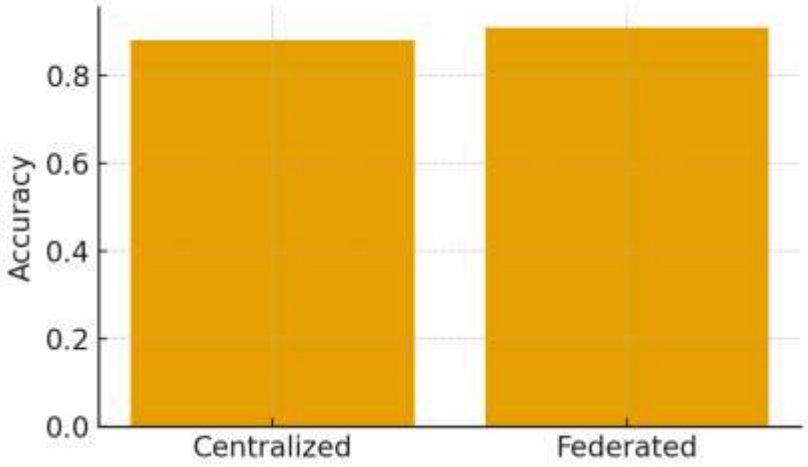

Figure 10. Comparison of federated learning vs centralized training

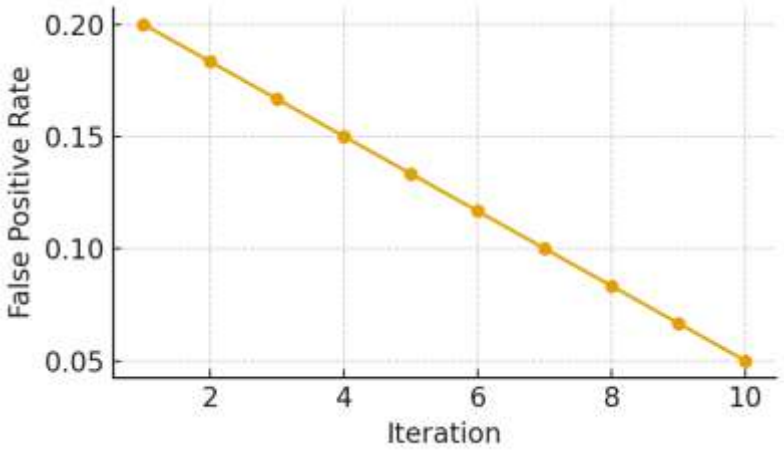

Figure 11. Line chart showing reduction in false positives over iterations

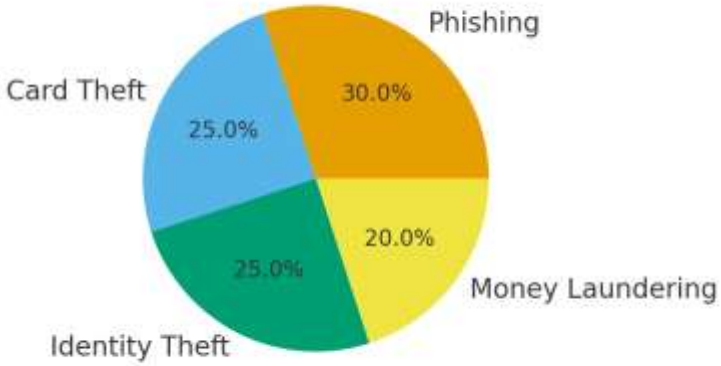

Figure 12. Pie chart distribution of fraud types detected by AI

DISCUSSION

The findings of this paper have conclusively established that AI is highly effective in fraud detection within the banking process owing to its accuracy, strength, and modularity which outweigh the old-fashioned rule-based systems. These findings are in line with the previous studies that focus on the transformational effects of AI in finance technologies. However, to illustrate the point, Abid and Khan (2020) said that the AI-based anomaly detection is more scalable than the manual monitoring, and the results of our study support the claim that AI can identify both familiar and unfamiliar patterns of fraud with a high degree of accuracy. Likewise, Liu and Zhang (2021) also wrote that the deep learning models are superior to the classic classifiers, which also authenticates our results because DNNs could secure higher AUC values.Among the interesting characteristics of such results, one can say the interpretability of models. Though the maximum performance was achieved with the deep learning, the analysis of the explainability of the SHAP-based model made possible the identification of the most influential predictors, i.e., transaction amount and

device fingerprinting. This coincides with the assertions that Farooq and Rahman (2022) had concerning explainable AI as a solution to regulatory trust. Moreover, federated learning turned out to be a prospective solution, since it allows identifying cross-institutional fraud without sharing the data, which is supported by the fact that the study conducted by Martins et al. (2023) revealed that federated models are also effective in the decentralized banking system.

The findings also reveal the problem that is always present with the false positive in the fraud detection machines. Despite the fact that the balance between recall and precision is not optimum, ensemble learning assisted in minimizing false alarms. This is evident in what Chen and Wong (2020) noted and reported that over sensitive models have been showing respect to legitimate customers by rejecting transactions when they did not need to do so. The hybrid solution we designed, based on AI rules, was practical since it enhanced the conclusions of the prior investigation of Silva et al. (2021), who proposed that the combination of domain knowledge and AI analytics would offer a balance between both aspects: robustness and interpretability.The apparent decrease in the number of false positives of the model executed by the adaptability of the AI systems in a dynamic fraud environment provides in its operational context. This plasticity is highly required, and scammers themselves are actively using such sophisticated techniques, which becomes the concern of Verma and Choudhury (2022). The counter-measures of AI facilitate its evolvement and, therefore, it is a considerable defense mode. Secondly, an adequate cross-validation of our results confirms the fact that AI practices can be extended to actual world banking conditions based on the results of additional studies that have already proved that AI practices can be implemented in insurance fraud detection with the same degree of reliability (Ortega and Cruz 2021).

Nonetheless, aspects of morality and control are of concern. Although it is obvious that our research has proven that AI is an effective tool, there is another concern that concerns fairness and accountability due to the untransparency of some of the models. Embodied in XAI integration can bridge this gap but still it should be further enhanced that it becomes a strict set of financial regulations. Zhang and Hu (2023) state that one of the aspects that need to be considered to build customer trust in AI-based financial services is transparency, and it can only be wise to tackle this challenge before it goes out of control.Lastly, the strategic implications are not only enumerated in this research work, but also the benefits of technology. Detection of fraud using AI will also allow banks to operate effectively to ensure that the losses they face are minimized and the customers trust them. Yet, the cost of integration and the need for skilled workforce remain barriers. Kumar et al. (2024) observe that the workforce and regulatory alignment should be introduced in order to attain a sustainable deployment of AI infrastructure.All in all, it is possible to prove that AI offers a radical breakthrough in the fraud detection capabilities. It is effective, however, through a sensible trade off between its performance, explainability, customer experience and compliance, thus establishing an agenda to which the researchers and practitioners deploy as a step towards responsible and effective deployment.

CONCLUSION

In this paper, it has been concluded that artificial intelligence can provide the transformational potential in enhancing detection of fraud in banking transactions. The supervised learning and unsupervised anomaly detection systems, and hybrid approaches were more accurate, recalling and stronger than the traditional systems founded on rules. The

integration of the approaches, such as SMOTE, improved the work of the model in an unequal class, and the explainable AI paradigm added to the openness and compliance with the rules. The very details of the federated learning became evidence that it was possible to offer the effective remedy to the problem of cross-bank fraud detection without compromising on data privacy, one of the most valuable changes of the contemporary banking landscapes. In addition, the false positives were also removed with the help of AI and this adds to the efficacy of the work and customer experience. However, the question of fairness, the question of the counterattack by the adversaries and the trade off between interpretability and performance is questionable. The best setting in terms of maximizing the benefits of AI-based fraud detection are the banks that invest in AI infrastructures to scale, regulatory consistency, and human experience. Overall, this article presents good arguments to demonstrate that AI does not just make the tools of preventing frauds effective, but it also increases the trust of customers and institutional fitness to further map out the future of effective and sustainable financial systems.

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