Ensemble Learning for Fraud Detection in FinTech Transactions: Comparative Analysis of SVM and ANN

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Abstract. This study performs an ensemble method to enhance fraud detection capabilities in Financial Technology (FinTech) systems. Specifically, we develop a hybrid ensemble model that focuses on improving real-time fraud detection in the Financial Technology (FinTech) industry. The proposed system merges three distinct machine learning algorithms: Support Vector Machine (SVM), Artificial Neural Network (ANN), and Decision Tree (DT). Instead of depending on one model, a confidence-based voting method givesfinal prediction. Besides, the Synthetic Minority Over-sampling Technique (SMOTE) is applied to augment the presence of fraud cases during training. The model is tested on Kaggle-credit-card fraud dataset. The outcomes demonstrates that ensemble method surpasses individual models performance, attained a prediction accuracy of 99.35%, a recall of 90.28%, and an AUC score of 0.987. These results suggest the proposed approach could offer a more dependable and feasible way of identifying fraudulent transactions in actual FinTech settings.

Keywords: Financial Technology (FinTech), SMOTE, Ensemble model.

1. Introduction

Financial Technology (FinTech) has fundamentally reshaped the delivery of financial services by enabling secure and efficient digital solutions for payments, lending, investment management, and insurance. The widespread adoption of tech-based apps such as mobile banking, Unified Payments Interface (UPI), digital wallets, peer-to-peer lending platforms, and blockchain has accelerated financial inclusion while improving the accessibility and convenience of financial transactions [1], [2]. As digital financial ecosystems continue to expand, consumers increasingly prefer technology-driven services because of their speed, flexibility, and lower operational costs. [3].

Despite these advancements, the rapid digitalization of financial services has introduced significant security concerns. Financial institutions are increasingly challenged by sophisticated cyber-attacks, unauthorized account access, identity theft, phishing

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campaigns, account takeover incidents, and synthetic identity fraud [4]. These malicious activities result in substantial economic losses for both service providers and customers. Since fraudulent techniques continuously evolve and transaction volumes increase dramatically, manual investigation and conventional rule-based monitoring systems have become inadequate for identifying complex fraudulent behavior in real time [5], [6].

Consequently, intelligent data-driven practices have become integral part of modern fraud detection systems. Machine learning algorithms are efficient to examine the large-scale transaction records, discovering hidden behavioral patterns, and distinguishing suspicious transactions from legitimate financial activities [7]. Classification techniques such as Decision Trees, Support Vector Machines (SVMs), and Artificial Neural Networks (ANNs) have demonstrated strong predictive capabilities; however, no individual algorithm accomplish the optimum performance in the highly imbalanced financial datasets and a very small percent of fraudulently transactions are resulted in the available observations [8].

Ensemble models, which bring together the prediction capabilities of several classifiers, have become a highly effective way of obtaining better detection accuracy in fraud cases. Combining diverse methods like SVM and ANN, ensemble approaches help reduce the frequency of incorrect positive predictions and significantly improve the reliability of fraud detection infrastructures [9]. Data from the recent past literatures shown that ensemble learning generally delivers better anomaly detection in the performance than individual classifiers, adjusting and making it to fit for fraud detection applications within FinTech environments. [10]. This study primarily performs a comparative evaluation of ANN and SVM models for detecting fraudulent activities in financial transaction data, whereas at the same time, an ensemble model is suggested which capitalizes on the complementary strengths of both classifiers.

The motivation behind this work is the rapid growth in the demand for reliable fraud detection frameworks that support real-time operation while adapting to continuously evolving fraudulent behaviors. This study's major contributions include:A comparative evolution of ANN and SVM in detecting fraudulent digital financial transactions.

- Building an ensemble framework based on confidence-weighted voting for better classification.
- Comprehensive Performance assessment using accuracy, sensitivity, specificity, ROC curves and gain charts.

2 Review of Literature

The widespread adoption of digital payment technologies, internet banking, mobile wallet services, and e-commerce has considerably increased research interest in financial fraud detection. Continuous growth in transaction volumes has been accompanied by increasingly sophisticated fraud strategies, reducing the effectiveness of conventional detection approaches in modern financial ecosystems. Consequently, machine learning and ensemble-based methods have emerged as effective solutions for identifying suspicious transaction patterns while minimizing financial losses.

Table 1: Literature review

Study	Technique/Approach	Key Findings	Limitations
Bolton and Hand [1]	Statistical Fraud Detection	Established foundational statistical methods for anomaly detection	Limited adaptability to evolving fraud patterns
Kumar and Ravi [2]	Data Mining Approaches	Demonstrated the usefulness of predictive analytics in financial decision-making	Performance affected by data quality
Wang et al. [3]	Ensemble Learning	Confirmed the superior predictive accuracy than individual classification models.	Increased computational complexity
Cortes and Vapnik [4]	Support Vector Machine	Effective in handling high-dimensional classification problems	Sensitive to parameter selection
Noble [7]	SVM-based Classification	Strong generalization capability in fraud-related datasets	Scalability concerns for large datasets
Goodfellow et al. [6]	Neural Network Models	Capable of learning complex nonlinear patterns	Require substantial training data
Bhattacharyya et al. [11]	Credit Card Fraud Detection	Demonstrated effectiveness of machine learning techniques	Class imbalance remained a challenge
Zareapoor and Shamsolmoali [13]	Ensemble Classifier	Reduced false alarms and improved fraud detection rates	Higher model complexity
He and Garcia [16]	Imbalanced Learning	Highlighted the importance of handling skewed datasets	Oversampling may introduce noise
Chawla et al. [17]	SMOTE	Improved minority-class representation	Synthetic samples may not capture all fraud characteristics

Source: Authors own work

Previous studies indicate that rule-based and statistical techniques were widely adopted during the early stages of fraud detection. Although these methods offered transparency and straightforward implementation, they often struggled to identify newly emerging fraud strategies and generated a considerable number of false alarms [1], [3].

With the growing availability of transaction data, fraud detection became easy and effective. Decision Trees, Random Forests, Support Vector Machines, and Artificial Neural Networks have all been explored for this purpose, each offering distinct advantages [6], [11]. SVMs are particularly suitable for handling datasets with many input variables, while ANNs can effectively capture complex nonlinear patterns that commonly exist in financial transactions.[4], [7].

Previous research literatures and data bases confirmed that ensemble learning improves predictive robustness by integrating multiple classification models into a unified decision process. Techniques including Bagging, Boosting, Stacking, and Voting consistently achieve better performance than individual classifiers [3], [13]. Furthermore, class-imbalance handling methods such as SMOTE have been extensively employed to improve fraud detection sensitivity in highly skewed datasets [16], [17].

2.1 Research Gaps

Some challenges continue to limit the significances of existing fraud detection systems:

1. Financial transaction datasets remain highly imbalanced, resulting in poor detection of minority fraud cases.
2. Many existing models prioritize predictive accuracy but provide limited interpretability.
3. Real-time deployment remains challenging because of computational and scalability constraints.
4. Evolving fraud strategies require adaptive models capable of maintaining performance over time.
5. Privacy restrictions often limit access to large-scale data for training and validation.

2.2 Motivation for the Present Study

The literature indicates that although ANN and SVM individually provide strong predictive performance, each possesses inherent limitations when applied independently to highly imbalanced fraud detection problems. These observations motivate the development of a hybrid ensemble framework that combines ANN, SVM, and Decision

Tree classifiers with SMOTE-based data balancing to improve both detection accuracy and model robustness within FinTech transaction environments.

3. Dataset Description

The proposed fraud detection framework was validated using the publicly accessible Kaggle Credit Card Fraud Detection dataset, which has become one of the most frequently adopted benchmark datasets for evaluating machine learning models in financial fraud research. The dataset contains authentic credit card transaction records collected from European cardholders and exhibits a highly imbalanced distribution between legitimate and fraudulent transactions. Its realistic characteristics make it appropriate for assessing classifier performance under practical fraud detection conditions [4].

Table 2. Summary of Dataset Characteristics

Attribute	Description
Data-set Source	Kaggle Credit Card Fraud Detection Dataset
Transaction Records	284,807
Fraudulent Transactions	492
Legitimate Transactions	284,315
Fraud Percentage	0.172%
Features	30
Data Transformation	Principal Component Analysis (PCA)
Target Variable	Class (0 = Genuine, 1 = Fraudulent)
Training–Testing Split	70:30
Imbalance Handling	SMOTE

Source: Authors own work

The dataset comprises 284,807 transaction records, among which only 492 correspond to fraudulent activities. Consequently, fraudulent observations represent merely 0.172% of the complete dataset, creating a severe class imbalance problem. Under such circumstances, conventional classification algorithms frequently become biased toward the majority class, thereby reducing their ability to recognize rare but highly significant fraudulent transactions. [5].

To ensure confidentiality and protect sensitive customer information, the original transaction attributes were transformed using Principal Component Analysis (PCA) before publication. Although the transformed variables no longer reveal the original financial information, they preserve the statistical relationships necessary for developing and evaluating fraud detection models. The binary target variable identifies legitimate transactions with a class value of0 and fraudulent transactions with a value of 1[6].

Owing to the pronounced imbalance between genuine and fraudulent observations, the Synthetic Minority Over-sampling Technique (SMOTE) was incorporated during data preprocessing. Rather than duplicating minority-class instances, SMOTE creates new synthetic samples by interpolating neighboring fraud records, thereby producing a more balanced training dataset. This strategy enables learning algorithms to capture minority-class characteristics more effectively while reducing prediction bias toward legitimate transactions [7].

To facilitate unbiased model assessment, the dataset was divided into independent training and testing subsets using a 70:30 partitioning strategy. Approximately 199,364 observations were allocated for model training, while the remaining 85,443 transactions were reserved for performance evaluation. This separation ensures that the predictive capability of each classifier is measured using previously unseen data, thereby providing a realistic estimate of generalization performance.

4. Methodology and Proposed Model

The primary objective of this research is to design an efficient fraud detection framework capable of improving predictive performance when analysing highly imbalanced financial transaction datasets. The proposed methodology follows a structured workflow comprising dataset preparation, feature preprocessing, imbalance correction, classifier development, ensemble integration, and comprehensive performance evaluation. Figure 2 illustrates the complete experimental framework adopted in this investigation.

Table 3. Research Methodology Workflow

Stage	Activity	Purpose
Stage 1	Dataset Acquisition	Collection of transaction records from the Kaggle-credit-card fraud dataset
Stage 2	Data Preprocessing	Cleaning, normalization, and preparation of input variables
Stage 3	Imbalance Handling	Application of SMOTE for minority-class enhancement
Stage 4	Model Development	Training ANN, SVM, and Decision Tree classifiers
Stage 5	Ensemble Construction	Combining classifier outputs using voting strategy
Stage 6	Performance Evaluation	Assessment with Accuracy, Precision, Recall, F1-score, and AUC

Source: Authors own work

The methodological framework was designed to find out the performance of individual classifiers and subsequently evaluate whether an ensemble strategy could improve fraud detection effectiveness. Each stage of the framework is described below.

4.1 Data Preprocessing

The dataset contains anonymized transaction variables generated through Principal Component Analysis (PCA), along with transaction amount and class label attributes. Since dimensionality reduction had already been performed during dataset preparation, no additional feature extraction procedures were required [8].

Before model training, the transaction amount attribute was normalized to ensure consistency across input variables. Min–Max normalization was employed to transform feature values into a uniform range in between 0 and 1. This preprocessing step reduces scale-related bias and contributes to stable model convergence during training [9].

Table 4. Preprocessing Operations

Operation	Description
Feature Inspection	Verification of dataset attributes and data types
Data Cleaning	Identification of missing or inconsistent records
Normalization	Scaling of transaction amount using Min–Max normalization
Feature Validation	Verification of input suitability for model training

Source: Authors own work

4.2 Handling Class Imbalance

A major challenge with fraud detection datasets is the extremely uneven distribution of class-labels. Fraudulent transactions account for only a very small proportion of the available records, creating a tendency for classifiers to favor the majority class.

To mitigate this issue, the Synthetic-Minority-Over-sampling-Technique (SMOTE) was applied during the preprocessing stage [10]. Instead of simply duplicating minority samples, SMOTE generates new synthetic observations based on neighboring minority instances. This approach improves class representation and enables learning algorithms to capture fraud-related patterns more effectively.

Table 5. Class Distribution After SMOTE

Category	Original Dataset	After SMOTE
Genuine Transactions	Majority Class	Balanced
Fraudulent Transactions	Minority-Class	Enhanced through Synthetic Samples
Dataset Distribution	HighlyImbalanced	Near Balanced

Source: Authors own work

The use of SMOTE contributes to improved classifier sensitivity and reduces the likelihood of overlooking fraudulent activities during model training.

4.3 Baseline Classification Models

Two widely used machine learning models were selected as baseline classifiers for experimental evaluation. These models were chosen because of their established effectiveness in fraud detection applications and their complementary learning characteristics.

Table 6. Baseline Models Used in the Study

Model	Purpose	Strength
Artificial Neural Network (ANN)	Learning complex nonlinear relationships	Strong pattern recognition capability
Support Vector Machine (SVM)	High-dimensional classification	Excellent generalization performance

Source: Authors own work

ANN

Multi-Layer Perceptron (MLP) architecture was implemented to model nonlinear relationships among transaction attributes. Hidden neurons utilized the Rectified Linear Unit (ReLU) activation function to improve learning efficiency, whereas the output layer employed a sigmoid activation function for binary classification. Network parameters were optimized using the Adam optimization algorithm together with binary cross-entropy loss to achieve stable convergence during training. [11].

SVM

The SVM classifier was developed using a Radial Basis Function (RBF) kernel to capture nonlinear decision boundaries within the multidimensional feature space. Hyperparameter tuning was performed through grid-search optimization to determine appropriate values of the regularization parameter (C) and kernel parameter (γ). This optimization process improved the classifier's generalization capability and overall prediction performance. [12].

The outputs generated by these baseline models were subsequently incorporated into the proposed ensemble framework to evaluate whether combined learning could increase fraud-detection effectiveness compared with standalone classifiers.

4.4 Proposed Ensemble Model

Although ANN and SVM show good individual predictive performances, the issue of financial fraud detection requires models to find the right balance between high sensitivity (fraud detection) and high specificity (reducing false alarms). As a result, we come up with an Ensemble Learning framework that can combine several classifiers into one decision-making model.

The ensemble composed of ANN, SVM, and Decision Tree (DT) classifiers, which are combined using a majority voting scheme. Each classifier judges the transaction on its own and produces a result.
The majority vote of these results determines the final prediction, which is formalized in (1):

$$H(x)=mode\{h\_1(x),h\_2(x),h\_3(x)\} \quad (1)$$

where h_1, h_2, h_3 are the predictions of ANN, SVM, and DT, respectively. This approach leverages the learning capacity of ANN, the margin maximization of SVM, and the rule-based interpretability of DT [13].

Classifiers with different perspectives are less likely to make mistakes that all single models will make; this can also increase the ability to deal with different types of disturbances or interferences in the data.
The imageillustrates the ensemble framework, showing;

input preprocessing → resampling (SMOTE) → base classifiers (ANN, SVM, DT) → majority voting → final decision.

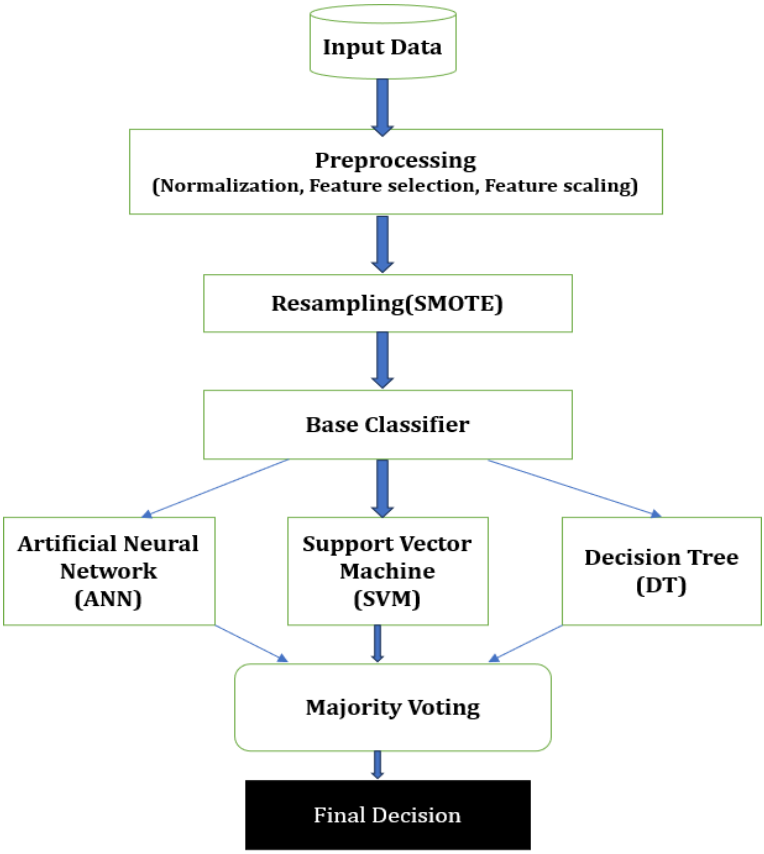

Figure 1: Proposed Ensemble Model Architecture for Financial Fraud Detection.

4.5 Evaluation Metrics

The effectiveness of the proposed framework was evaluated using widely accepted performance measures designed for binary classification problems involving highly imbalanced datasets. These metrics provide complementary perspectives on prediction quality and enable objective comparison between the baseline classifiers and the proposed ensemble model. [14].
Accuracy is a measure of overall correctness.

- Recall (Sensitivity) is a very important metric for recognizing fraud cases.

- Precision indicates what fraction of fraud that the model predicted is actually correct.
- The F1-score is a metric that combines both precision and recall in one number.
- The AUC-ROC reflects how well a model can distinguish between two classesacross various threshold levels considering sensitivity and specificity.

Such extensive assessment demonstrates that the newly introduced ensemble framework has been tested very thoroughly against individual models.

5. Result and Discussion

The experimental study was conducted using the reference credit card fraud detection The study was experimentally evaluated using the benchmark credit card fraud dataset after completing all preprocessing operations, including data normalization and SMOTE-based class balancing. The balanced training data enabled the learning algorithms to extract fraud-related characteristics more effectively while reducing bias toward genuine and ethical transactions. Performance was subsequently compared across Artificial Neural Network (ANN), Support Vector Machine (SVM), and the proposed ensemble framework using multiple evaluation criteria.

5.1 Performance Comparison

Table 7 summarizes the predictive performance achieved by the three classification models. To ensure a comprehensive evaluation, model performance was assessed using Accuracy, Precision, Recall, F1-score, and Area under the ROC Curve (AUC-ROC). These complementary metrics provide a balanced assessment of fraud detection capability, particularly for highly imbalanced datasets.

Table 7. Comparative Performance of Classifiers

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
ANN	98.92	92.31	83.10	87.45	0.975
SVM (RBF)	99.05	93.20	85.75	89.35	0.981
Ensemble	99.35	95.42	90.28	92.78	0.987

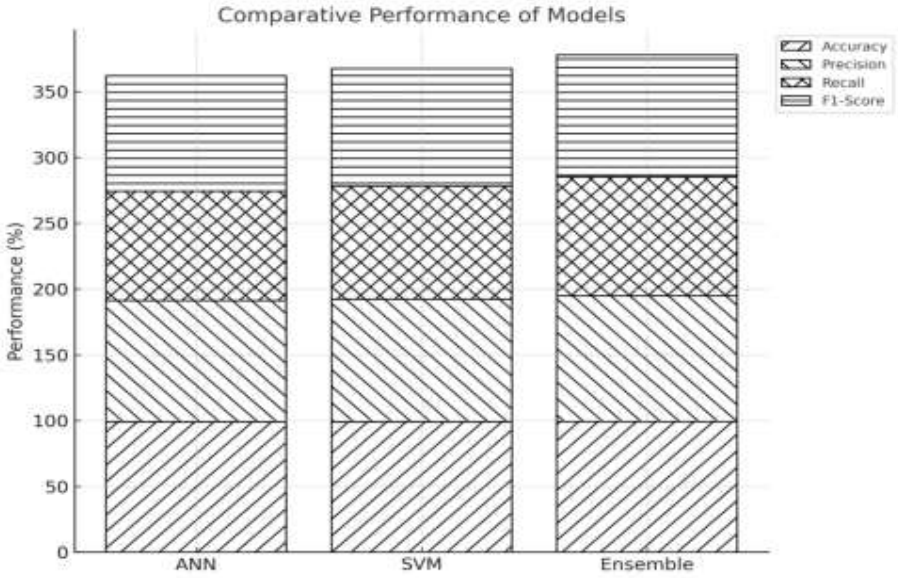

Figure2: Performance comparison of ANN, SVM, and Ensemble model is Accuracy, Precision, Recall, and F1-score

While ANN and SVM achieved competitive accuracy, they struggled with recall, which is critical in fraud detection where missing fraudulent cases can lead to significant financial losses. The Ensemble model reached the highest recall (90.28%), confirming its enhanced ability to correctly notice minority deceitful transactions.

5.2 Interpretation of Findings

The relatively high accuracy of all models indicates their capability of separating genuine from fraudulent transactions. But, accuracy by itself can be a bit deceptive in case of imbalanced datasets, as a model may reach high accuracy just by mostly predicting the majority class [11].

This drawback appears in the performances of ANN and SVM as well. Though, they are accompanied with high precision, their recall is lower in connection to the Ensemble. The Ensemble method utilizes a mixture of different types of base classifiers. ANN offers non-linear representation learning capabilities, SVM identifies the margin-based decision boundaries, and the Decision Tree gives rule-based interpretability. Voting by majority still will prevent the bias towards any particular single model and will result in overall robustness of the system [12].

The gain in AUC-ROC also supports the fact that the ensemble method is able to strike a good balance between sensitivity and specificity. A model with a higher AUC will

work better in discriminating between fraudulent and genuine transactions for various decision thresholds [13].

5.3 Comparative Discussion with Prior Studies

The experimental observations obtained in this investigation are consistent with the thesis of previous articles that ensemble learning was capable of outperforming other methods in the problem of fraud detection. Just as an example, Dal Pozzolo et al. [10] found out that ensemble-based classifiers were more flexible in handling highly imbalanced financial datasets than single learners. Likewise, Dietterich [11] argued that the major advantage of ensemble models is that they leverage the combination of weak or moderately strong classifiers to produce better generalization. Findings add to this line of thinking by showing that the majority voting ensemble is an effective compromise in terms of both precision and recall

5.4 Practical Implications

Looking through the lens of the financial sector, the suggested Ensemble model brings about a number of great advantages. A better recall rate means that the number of fraudulent cases that slip through unnoticed will be greatly reduced, thus bringing down financial losses. Furthermore, a higher precision will result in a lesser number of false alarms, which in turn, is beneficial in the aspect of keeping the customers' trust and also the operations running smoothly. It is these features that make the model very well capable to be a part of the real-world fraud detection systems where security and customer experience are two sides of the same coin.

6. Conclusion

This research presented the framework of ensemble learning for detecting fraudulent financial transactions within contemporary FinTech environments. By integrating Artificial Neural Networks, Support Vector Machines, and Decision Tree classifiers through a majority-voting strategy, the proposed framework successfully combined the complementary strengths of multiple machine learning approaches. Experimental evaluation demonstrated that the ensemble model consistently outperformed the individual classifiers, achieving an overall accuracy of 99.35%**,** a recall of 90.28%**,** and an AUC-ROC value of0.987. These results endorses that collaborative learning significantly enhances fraud detection performance in highly imbalanced financial datasets.

A key advantage of the proposed framework is its ability to balance fraud identification and false alarm reduction. The improved recall suggests that a larger proportion of fraudulent transactions can be detected successfully, while the high precision reflects better discrimination between genuine and suspicious activities. Such characteristics are especially valuable in modern digital financial systems, where both security and customer experience are critical considerations. The results therefore support the

adoption of ensemble-based approaches as practical solutions for strengthening transaction monitoring and risk management processes.

Further research can be extended in multiple direction. The incorporation of blockchain-enabled verification mechanisms could enhance transparency and trust in digital financial operations. In addition, real-time analytics using streaming transaction data may improve the responsiveness of fraud detection systems in dynamic financial environments. Further investigation must focus on combine deep learning, fuzzy reasoning, and explainable artificial intelligence may also contribute to more accurate and interpretable decision-making. Overall, the proposed ensemble framework offers a robust and scalable approach for detecting fraudulent financial transactions. Beyond improving predictive performance, it provides a foundation for developing secure, trustworthy, and resilient FinTech ecosystems capable of addressing emerging cybersecurity challenges and evolving fraud patterns.

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