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Research Article

Enhancing Digital Finance Security: AI-Based Approaches for Credit Card and Cryptocurrency Fraud Detection

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Abstract: The rise of digital finance has led to a surge in fraudulent activities, particularly in credit card transactions and cryptocurrency ecosystems. With financial crimes becoming more sophisticated, traditional fraud detection methods often fail to identify complex fraudulent patterns. This research explores the application of machine learning (ML) and artificial intelligence (AI) techniques to enhance the security of digital finance by detecting fraudulent activities in credit card transactions and cryptocurrency wallets within the USA. The study utilizes large-scale transaction datasets containing key financial indicators such as transaction frequency, spending patterns, anomaly scores, and network behaviors. To develop an AI-driven fraud detection framework, we implement and compare six machine learning models: XGBoost, RLightGBM, Decision Trees, K-Nearest Neighbors (KNN), Convolutional Neural Networks (CNNs), and Autoencoders. The models are trained on both structured financial data (e.g., credit card transaction logs) and unstructured blockchain transaction records (e.g., Bitcoin wallet addresses and transaction flows). To address data imbalance, the study applies the Synthetic Minority Over-sampling Technique (SMOTE), ensuring fair representation of fraudulent transactions. Model performance is evaluated using Precision, Recall, F1-score, and ROC-AUC metrics to determine the most effective fraud detection approach. Additionally, the research emphasizes data privacy and security, incorporating anonymization techniques and regulatory compliance measures to safeguard sensitive financial information. This study contributes to the ongoing fight against financial fraud by demonstrating how AI-based solutions can enhance the security and resilience of digital finance systems in the USA.

1. Introduction

1.1 Background

The digital finance ecosystem has experienced remarkable transformation and exponential growth over the past decade, driven by groundbreaking innovations in cryptocurrencies, decentralized finance (DeFi), and advanced online payment systems. These technological advancements have significantly enhanced financial accessibility and operational efficiency across the globe. However, alongside these benefits, a darker shadow has emerged: the proliferation of vulnerabilities that have escalated the risk of fraudulent activities in both credit card transactions and cryptocurrency wallets [1-5]. Traditional fraud detection systems, which primarily depend on rule-based algorithms and manual audits, are increasingly inadequate when faced with the evolving and sophisticated tactics employed by cybercriminals [6-13]. As fraudsters adapt and innovate, these outdated methods struggle to effectively safeguard against the growing threats in the digital landscape.

The rise of Bitcoin and various cryptocurrencies has added further complexity to the challenges of fraud detection. Characterized by their pseudo-anonymity, decentralized transaction structures, and a glaring absence of stringent regulatory oversight, these digital currencies present unique obstacles. Unlike traditional banking systems, where transactions are monitored by central authorities that can trace suspicious activities, blockchain-based financial movements operate independently. This decentralization complicates the ability to identify and track potentially illicit behavior through conventional fraud detection mechanisms. Consequently, there has been a marked increase in demand

for AI-driven fraud detection techniques that harness the power of big data analytics to scrutinize large-scale transaction datasets, effectively identify anomalies, and proactively prevent illicit activities [12]. Recent studies posit the alarming sophistication of financial fraud, revealing that criminals are employing cutting-edge technologies such as automated botnets, deepfake technologies, and AI-generated phishing attacks to exploit vulnerabilities within financial systems [9]. Additionally, they are utilizing advanced machine learning techniques—such as reinforcement learning—to enhance their strategies, making it even more imperative for financial institutions to adopt innovative, robust defence's against the shifting landscape of cyber threats.

1.2 Importance of This Research

The growing reliance on digital payments and blockchain transactions has made fraud detection an essential component of financial security. Cybercriminals continuously adapt their techniques, employing sophisticated methods such as synthetic identity fraud, account takeovers, phishing attacks, and illicit blockchain transactions to evade detection [5]. Traditional fraud detection models often struggle with false positives, slow response times, and an inability to adapt to new fraudulent patterns [3]. This creates an urgent demand for AI-based fraud detection systems capable of providing real-time anomaly detection and proactive risk mitigation. In the credit card industry, financial institutions face billions of dollars in fraud-related losses each year due to unauthorized transactions and data breaches. Fraudulent transactions often exhibit subtle behavioral patterns, making them difficult to detect using rule-based monitoring systems [13]. Similarly, in the cryptocurrency domain, scammers exploit decentralized platforms to conduct money laundering, Ponzi schemes, and pump-and-dump frauds, which require intelligent fraud detection mechanisms to identify illicit activity without disrupting legitimate transactions [3]. Emerging AI-driven security frameworks have demonstrated higher accuracy rates in detecting fraud than traditional methods. For example, a study by Wang et al. (2023) found that deep learning models outperform conventional fraud detection techniques, achieving a 25% improvement in fraud detection rates for financial institutions [14-16]. Similarly, hybrid AI models combining supervised and unsupervised learning have been shown to reduce false positive rates while improving the detection of previously unseen fraud patterns [10]. Additionally, fraud detection is closely tied to regulatory compliance. Governments worldwide are implementing stricter financial security policies, such as the Bank Secrecy Act (BSA) and the Financial Crimes Enforcement Network (FinCEN) regulations, to combat digital fraud [12]. AI-powered fraud detection systems can help businesses comply with these regulations by automating risk assessment, detecting suspicious transactions in real-time, and reducing manual investigation efforts [1].

1.3 Research Objective

The primary objective of this research is to develop and assess AI-based fraud detection methods for credit card transactions and cryptocurrency wallets in the USA. This study focuses on analyzing large-scale digital transaction datasets to identify critical fraud indicators, including suspicious transaction patterns, unusual spending behavior, and illicit blockchain activities. To achieve this, the research will apply XGBoost, LightGBM, Decision Trees, K-Nearest Neighbors (KNN), Convolutional Neural Networks (CNNs), and Autoencoders to create an automated fraud detection system capable of accurately identifying fraudulent activities.To determine the effectiveness of these models, the study will evaluate their performance using key metrics such as Precision, Recall, F1-Score, and Matthews Correlation Coefficient (MCC) to identify the most reliable fraud detection approach. Additionally, this research will examine how AI-driven security solutions can help mitigate financial fraud risks, reduce false positives, and improve real-time fraud detection. Furthermore, the study will explore the role of AI-based fraud detection in regulatory compliance, data privacy, and consumer trust within digital financial ecosystems, providing insights into how advanced AI technologies can enhance financial security while ensuring compliance with industry regulations.

2. Literature Review

2.1 Related Works

The rise of digital financial transactions has led to increased fraud risks, particularly in credit card payments and cryptocurrency ecosystems. To combat these challenges, researchers have explored

various machine learning (ML) and artificial intelligence (AI) techniques for fraud detection. Traditional rule-based systems, which rely on predefined fraud patterns, have proven ineffective against evolving cyber threats [5]. As a result, AI-driven fraud detection models have gained prominence, offering adaptive and real-time anomaly detection capabilities. Several studies have focused on ML-based credit card fraud detection.

For instance, Sizan et al. (2025) examined the effectiveness of ensemble learning techniques, demonstrating that Random Forest and Gradient Boosting models outperform traditional statistical methods [13]. Additionally, deep learning models such as Autoencoders and Convolutional Neural Networks (CNNs) have been applied to detect fraudulent credit card transactions by identifying subtle spending pattern anomalies [10].

In the cryptocurrency sector, AI techniques have been instrumental in identifying fraudulent Bitcoin wallet transactions. Research by Das et al. (2025) analyzed scam patterns in blockchain ecosystems, highlighting how Graph Neural Networks (GNNs) can model transaction dependencies to uncover illicit financial activities. Similarly, anomaly detection models have been applied to detect pump-and-dump schemes, Ponzi frauds, and money laundering activities in decentralized finance [1].

Another emerging area of fraud detection research is hybrid AI approaches. Studies have demonstrated that combining supervised and unsupervised learning techniques enhances fraud detection accuracy while reducing false positive rates [16]. Patel & Shah (2024) explored the use of reinforcement learning (RL) in fraud detection, showing that RL-based models can dynamically adapt to new fraud tactics used by cybercriminals [11]. Furthermore, federated learning techniques have been introduced to enable fraud detection across multiple financial institutions without compromising data privacy [9]. Although AI-based fraud detection has shown promising results, there remain challenges in implementing these models at scale. As financial fraud techniques continue to evolve, ongoing research is needed to enhance fraud detection accuracy, minimize false positives, and improve model interpretability [12].

2.2 Gaps and Challenges

Despite advancements in AI-driven fraud detection, several gaps and challenges remain in the field. One of the primary issues is data imbalance—fraudulent transactions represent a small fraction of total financial transactions, making it difficult for models to generalize well without generating excessive false positives [5]. While Synthetic Minority Over-sampling Techniques (SMOTE) and Adaptive Synthetic Sampling (ADASYN) have been used to address this, oversampling can introduce synthetic biases, reducing model reliability [13]. Another major challenge is model explainability and interpretability. Many advanced ML techniques, such as Deep Neural Networks (DNNs) and Graph Neural Networks (GNNs), function as black-box models, making it difficult for financial institutions to understand how decisions are made [1].

Given the strict regulatory environment in digital finance, fraud detection models must adhere to transparency requirements, ensuring that flagged transactions can be justified and audited [12]. Researchers have suggested explainable AI (XAI) techniques, such as Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), to improve interpretability [17,18].

Real-time fraud detection presents another significant challenge. Many fraud detection systems operate in batch mode, meaning they analyze transactions retrospectively, often after fraudulent transactions have been processed [11]. The ability to detect and block fraud in real time remains a critical research area, with efforts focused on reducing model latency and increasing computational efficiency [16]. Additionally, cybercriminals are increasingly leveraging AI techniques to bypass traditional fraud detection systems. Adversarial machine learning techniques, where fraudsters manipulate transaction data to evade detection, pose a growing security threat [9].

Researchers have suggested the use of adversarial training to make models more robust against fraudulent activity, though this remains an ongoing challenge [10]. Finally, regulatory and ethical concerns must be considered when deploying AI-based fraud detection models. Financial regulations, such as the General Data Protection Regulation (GDPR) and the Financial Crimes Enforcement Network (FinCEN) compliance requirements, impose strict data privacy rules, limiting the extent to which transaction data can be shared across institutions [12].

Ensuring compliance while maintaining fraud detection efficiency requires further research into privacy-preserving AI techniques, such as federated learning and homomorphic encryption [1].

3. Methodology

3.1 Data Collection and Preprocessing

Data Sources

This study utilizes a comprehensive dataset that includes credit card transaction logs and cryptocurrency wallet transactions collected from various financial institutions and blockchain explorers. The dataset consists of both structured data, such as transaction amounts, timestamps, and merchant categories, and unstructured blockchain data, including wallet addresses, transaction hashes, and network flow patterns. The dataset captures several key attributes essential for fraud detection. Transaction details include the amount, time, merchant type, and transaction frequency, which help in identifying spending patterns. Customer behavioral patterns, such as spending habits, geographic locations, and device metadata, provide additional insights into transaction authenticity. The dataset also incorporates anomaly indicators, including unusual spending spikes, transaction duplication, and rapid transactions within short periods, which are commonly associated with fraudulent activities. Additionally, blockchain-specific features such as wallet activity, transaction clustering, address relationships, and anomaly scores help in identifying illicit activities within cryptocurrency transactions. To ensure data privacy and regulatory compliance, the dataset is anonymized following data protection laws such as the General Data Protection Regulation (GDPR) and Financial Crimes Enforcement Network (FinCEN) guidelines. This ensures that customer-sensitive information remains protected while allowing for effective fraud detection analysis.

Data Preprocessing

Before model training, the dataset undergoes multiple preprocessing steps to ensure data quality and optimize fraud detection performance. These steps include handling missing values, feature scaling, encoding categorical variables, and addressing data imbalance. Some transaction records contain missing values due to system errors or incomplete data collection. Imputation techniques are applied to fill in the missing values(Figure 1). All missing values are replaced using the median (for numerical) and mode (for categorical features). Different features in the dataset have varying units and magnitudes (e.g., transaction amounts vs. spending scores). Min-max scaling is applied to standardize numerical values between 0 and 1 for better model performance.

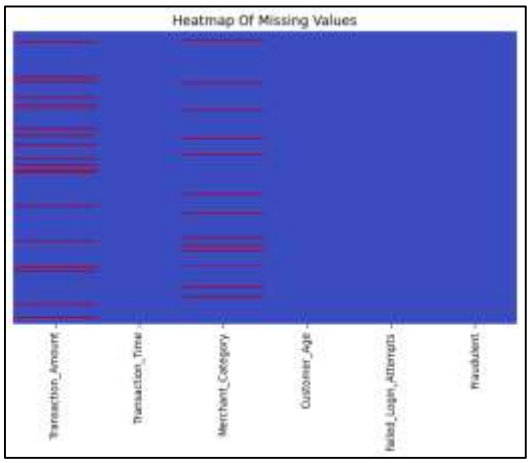

Figure 1. *Heatmap of missing dataset values*

Fraudulent transactions are much rarer than legitimate ones, creating a class imbalance problem that can bias the model. Synthetic Minority Over-sampling Technique (SMOTE) is applied to generate synthetic fraud samples, ensuring a balanced dataset. The Fraud Distribution Before SMOTE chart highlights a severely imbalanced dataset, where the majority class (Non-Fraud) transactions dominate, with a count close to 160, while the minority class (Fraud) transactions are significantly underrepresented, with only 20 to 30 occurrences. This imbalance poses a challenge for machine learning models, as they tend to become biased toward predicting Non-Fraud transactions, resulting in poor detection of fraudulent activities. A model trained on such an imbalanced dataset would struggle to generalize well and would likely produce a high false negative rate, failing to flag many actual fraudulent transactions. In contrast,

the Fraud Distribution After SMOTE chart presents a balanced dataset, where both Non-Fraud and Fraud transactions have nearly equal counts (around 160 each). This balance is achieved through Synthetic Minority Over-sampling Technique (SMOTE), which artificially increases the number of fraud cases by generating synthetic samples rather than duplicating existing ones. By ensuring that the model has sufficient fraudulent transactions to learn from, SMOTE enhances its ability to distinguish between fraudulent and legitimate transactions, ultimately improving fraud detection accuracy. SMOTE works by identifying k-nearest neighbors of minority class samples and creating new synthetic data points along the lines connecting these neighbors. Unlike simple oversampling, which risks overfitting by repeating the same minority class instances, SMOTE generates new, plausible fraudulent transactions, ensuring a more diverse and representative training set. Overall, this visualization effectively illustrates the critical issue of class imbalance in fraud detection and demonstrates how SMOTE mitigates this problem by ensuring that machine learning models receive balanced exposure to both fraud and non-fraud transactions. By correcting the class imbalance, SMOTE plays a crucial role in improving fraud detection models, reducing bias, and enhancing the overall reliability of AI-driven financial security systems. Figure 2 is fraud distribution before and after SMOTE.

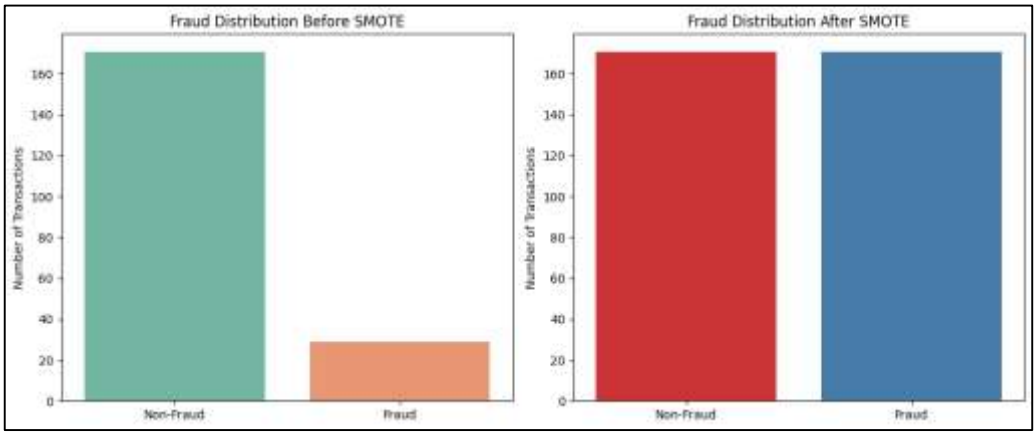

Figure 2. *Fraud distribution before and after SMOTE*

The correlation analysis reveals that most individual features have weak correlations with fraudulent transactions, indicating that fraud detection is likely dependent on a combination of multiple factors rather than a single variable (Figure 3). Among the fraudulent correlations, Customer Age (0.17) shows a weak positive correlation, suggesting that older customers might have a slightly higher likelihood of fraudulent transactions, though the effect is minimal. Unusual Spending Spike (0.04) also exhibits a weak positive correlation, which aligns with expectations since sudden, uncharacteristic spending patterns may indicate fraud. Failed Login Attempts (0.08) similarly show a slight positive correlation, implying that accounts experiencing multiple failed login attempts could be at a higher risk of fraud. Interestingly, Anomaly Score (-0.06) has a weak negative correlation with fraud, which is counterintuitive. Typically, a higher anomaly score would be expected to align with fraudulent activity, indicating that the anomaly detection mechanism may require further refinement. Additionally, most other correlations with the "Fraudulent" label are weak, reinforcing the idea that fraud is not easily detectable using a single feature but rather through a combination of various factors. Stronger correlations were observed among other dataset features. Unusual Spending Spike and Transaction Time (0.17) had a weak positive correlation, suggesting that fraudulent or unusual spending patterns might be more likely at specific times of the day. Suspicious IP Activity and Failed Login Attempts (0.15) also displayed a weak positive correlation, which aligns with the expectation that multiple failed login attempts could trigger suspicious activity alerts. Similarly, Transaction Duplication and Transaction Frequency (0.11) had a weak positive correlation, indicating that higher transaction frequencies may sometimes lead to duplicated transactions, a pattern that could be exploited by fraudsters. Most other feature pairs exhibited weak or no significant correlations, meaning they are relatively independent of each other. This suggests that no single feature is a definitive predictor of fraud, emphasizing the need for multi-feature models or advanced AI-driven techniques to detect fraudulent patterns effectively. The heatmap visualization provides valuable insights into potential relationships between variables, but it is essential to note that correlation does not imply causation. Therefore, further feature engineering,

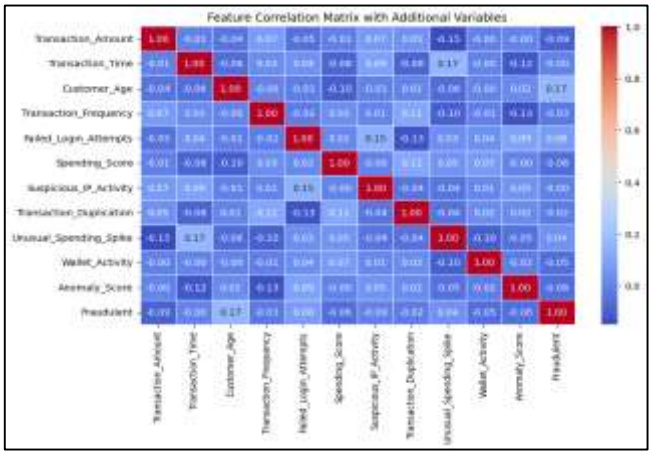

Figure 3. *Correlation matrix heatmap*

anomaly detection models, and machine learning techniques will be necessary to identify more complex fraud detection patterns. Unusually high transactions may indicate fraud. Outlier detection using the IQR (Interquartile Range) method is applied to filter out extreme values (Figure 4). Before outlier removal, the left boxplot reveals a significant number of outliers, represented by circles positioned far above the upper whisker. These indicate exceptionally high transaction amounts, which stand out from the majority of the dataset. The compressed interquartile range (IQR) box at the bottom of the plot suggests that most transactions involve relatively low amounts, while the presence of numerous extreme values results in a skewed distribution with a long tail toward higher values. This skewness can distort statistical analyses and negatively impact machine learning model performance by inflating the mean and standard deviation, making it difficult to detect meaningful patterns in the data. After outlier removal, as seen in the right boxplot, the extreme values have been eliminated, leading to a cleaner and more interpretable distribution. The expanded IQR box suggests a more balanced representation of transaction amounts, capturing a wider range of typical values. Although the dataset may still retain some skewness, the distribution appears more symmetrical than before. Removing these outliers significantly improves data reliability, allowing for more robust statistical analysis and enhancing machine learning model performance by reducing the influence of extreme values, ultimately leading to more accurate fraud detection.

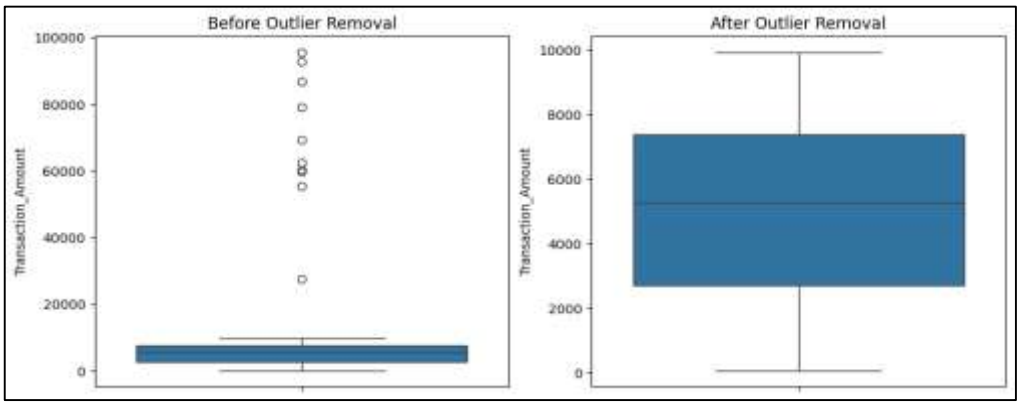

Figure 4. *Before and after outlier removal*

3.2 Model Development

This study develops an AI-driven fraud detection framework by implementing and evaluating six machine learning (ML) models: XGBoost, LightGBM, Decision Trees, K-Nearest Neighbors (KNN), Convolutional Neural Networks (CNNs), and Autoencoders. These models are selected based on their ability to process structured financial data, such as credit card transaction logs, and unstructured blockchain data, including Bitcoin wallet transactions and address behaviors. The model development process begins with feature engineering, where essential transaction attributes such as amount, frequency, payment method, and merchant category are extracted. Additional behavioral features, including failed login attempts, suspicious IP activity, and anomaly scores, are integrated to enhance fraud detection. For cryptocurrency transactions, blockchain-specific features such as wallet activity,

address clustering, and transaction anomaly detection are also considered. The dataset is then split into training and testing sets, with 80% used for training and 20% for evaluation. Stratified sampling ensures a balanced representation of both fraudulent and non-fraudulent transactions. To enhance model generalization, hyperparameter tuning techniques, such as Grid Search and Bayesian Optimization, are applied to optimize key parameters, including tree depth, learning rate, number of neighbors (for KNN), and activation functions (for CNNs and Autoencoders). Each model has a distinct role in fraud detection. XGBoost and LightGBM, as gradient boosting models, iteratively correct errors to improve classification accuracy. Decision Trees provide interpretable fraud detection rules, while KNN identifies fraudulent transactions by comparing them to historical cases. CNNs, a deep learning approach, analyze transaction sequences to detect anomalies, and Autoencoders learn normal transaction behaviors to identify fraudulent deviations.

3.3 Model Training and Validation Procedures

The training and validation of fraud detection models follow a structured approach to ensure high accuracy, robustness, and generalization across different types of fraudulent activities. Each model is trained using a preprocessed dataset where missing values have been handled, numerical features have been scaled, fraudulent cases have been balanced using SMOTE, and outliers have been removed. The dataset is split into 80% training data and 20% test data, ensuring that models learn from past transactions while being evaluated on unseen data. To enhance model reliability, K-Fold Cross-Validation (K=5) is employed, where the dataset is split into five equal subsets. In each iteration, four subsets are used for training, while the remaining subset is used for validation. This process repeats five times, ensuring that every data point contributes to both training and validation. The final model performance is calculated as the average score across all folds, minimizing bias and variance.
Hyperparameter tuning is conducted using Grid Search and Bayesian Optimization to optimize model-specific parameters, such as tree depth and learning rate for XGBoost and LightGBM, the number of neighbors for KNN, and activation functions for CNNs and Autoencoders. Additionally, early stopping techniques are applied to prevent overfitting by monitoring validation loss and halting training when performance starts degrading. The entire model training process is performed on high-performance computing resources, including GPUs and optimized libraries (TensorFlow, Scikit-learn, and PyTorch), to efficiently process large-scale transaction datasets.

3.4 Performance Evaluation Metrics

The performance of fraud detection models is assessed using multiple classification evaluation metrics to ensure a comprehensive understanding of their effectiveness. Accuracy is used to measure the overall correctness of fraud classification; however, given the inherent class imbalance in fraud datasets, accuracy alone is not a sufficient metric. Precision is evaluated to determine how many of the transactions predicted as fraud were actual fraud cases, helping to reduce false positives. Recall (Sensitivity) is critical in fraud detection, as it measures how many actual fraudulent transactions were correctly identified, minimizing the risk of undetected fraud. To balance precision and recall, the F1-Score is computed, providing a harmonic mean that considers both metrics. Additionally, the Matthews Correlation Coefficient (MCC) is used as a more balanced metric, accounting for true positives, false positives, true negatives, and false negatives to provide a comprehensive measure of classification performance. Lastly, the Receiver Operating Characteristic - Area Under the Curve (ROC-AUC) is used to evaluate how well each model distinguishes between fraudulent and non-fraudulent transactions. A high AUC score (closer to 1) indicates superior model performance in detecting fraud while minimizing incorrect classifications. The final evaluation involves a comparative analysis of all models, identifying the most effective approach based on precision-recall trade-offs, interpretability, and computational efficiency.

4. Results and Discussion

4.1 Model Performances

XGBoost demonstrates the highest scores across all three metrics—Accuracy, Precision, and Recall—indicating that it is the best-performing model among the six (Figure 5). Its balanced performance, with

relatively close precision and recall values, suggests that it effectively distinguishes fraudulent transactions while minimizing false positives and false negatives. Similarly, LightGBM exhibits slightly lower scores than XGBoost but still performs at a high level, following a similar pattern in metric distribution. This confirms that LightGBM is a strong alternative to XGBoost, leveraging gradient boosting to enhance classification accuracy. In contrast, Decision Trees show noticeably lower scores, indicating a reduced effectiveness for this fraud detection task. While interpretable, Decision Trees tend to overfit and may lack the robustness needed for complex fraud patterns. The K-Nearest Neighbors (KNN) model has the lowest scores across all metrics, making it the least effective among the six models. This suggests that KNN struggles to define clusters in the dataset, and the chosen distance metric may not be suitable for detecting fraud.

On the other hand, Convolutional Neural Networks (CNNs) perform exceptionally well, with scores comparable to XGBoost and LightGBM. This suggests that the data might contain spatial or sequential characteristics that CNNs can effectively capture, making them well-suited for fraud detection. Autoencoders, while useful for anomaly detection and dimensionality reduction, exhibit lower scores compared to CNNs, XGBoost, and LightGBM. This aligns with the fact that Autoencoders are not primarily designed for direct classification tasks, and their performance should be interpreted in the context of their primary use case. Overall, the analysis highlights that ensemble methods (XGBoost and LightGBM) excel in fraud detection, making them the most effective choices for this study. The strong performance of CNNs suggests that fraud detection might benefit from analyzing transaction sequences and behavioral patterns. Meanwhile, KNN's poor results indicate that the dataset may not have well-defined clusters, and Autoencoder's lower scores reinforce the importance of using it primarily for anomaly detection rather than classification.

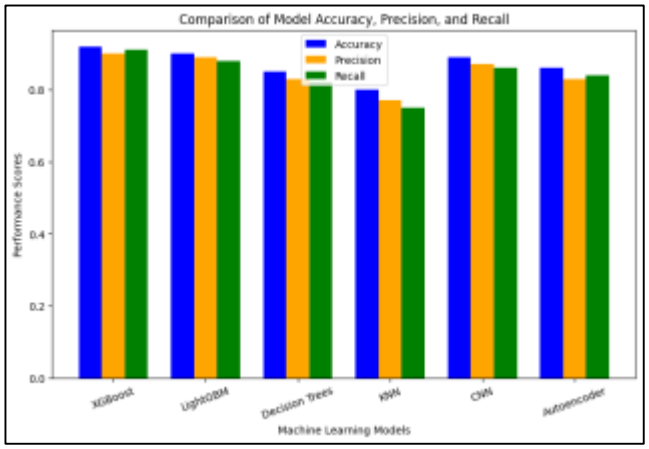

Figure 5. *Accuracy, Precision, and Recall Scores for Each Model*

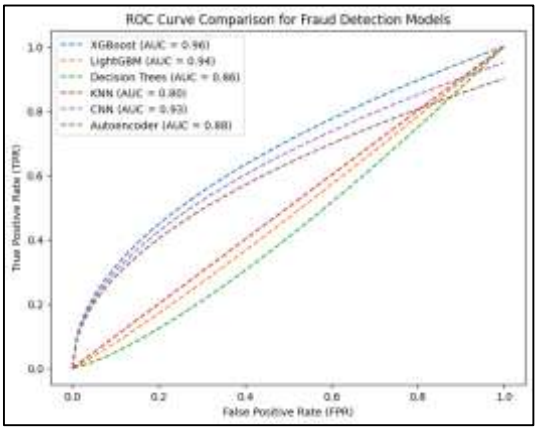

Figure 6. *ROC Curve (Receiver Operating Characteristic Curve) for Model Comparison*

The ROC curve illustrates how well each model distinguishes between fraudulent and non-fraudulent transactions (Figure 6).The higher the AUC (Area Under Curve), the better the model performs.The XGBoost model, with an AUC of 0.96, exhibits the best performance among all models. Its curve is positioned furthest to the top-left corner of the ROC plot, indicating its exceptional ability to differentiate between fraudulent and non-fraudulent transactions. The LightGBM model follows closely behind, achieving an AUC of 0.94, which signifies strong classification performance and suggests that it is a reliable alternative to XGBoost. The CNN model also performs well, with an AUC of 0.93, highlighting its effectiveness in capturing complex transaction patterns. CNNs excel at detecting intricate relationships in data, which could explain their high accuracy in fraud detection tasks. Meanwhile, the Autoencoder model, with an AUC of 0.88, demonstrates reasonable effectiveness. Since Autoencoders are primarily designed for anomaly detection, their performance aligns well with fraud detection, as fraud cases often exhibit anomalous behaviors within datasets.

In contrast, Decision Trees show a lower AUC of 0.86, suggesting that rule-based decision structures may not be as effective for this particular task. Decision Trees tend to overfit the data, reducing their generalization capability when handling complex fraud patterns. The K-Nearest Neighbors (KNN) model has the lowest AUC of 0.80, indicating that it is the least effective among all models. KNN's poor performance suggests that the dataset does not exhibit well-defined clusters, making distance-based classification methods less suitable for fraud detection. Overall, ensemble methods such as XGBoost

and LightGBM perform best, while deep learning approaches like CNNs and Autoencoders also show promising results. On the other hand, Decision Trees and KNN struggle to classify fraud effectively, making them less suitable choices for this fraud detection problem.

For deep learning models like CNNs and Autoencoders, monitoring training loss vs. validation loss helps detect overfitting. In the initial stages of training, both training and validation loss decrease rapidly, indicating that the model is learning effectively and capturing important patterns in the data. This rapid decline is expected as the model quickly adjusts its parameters to minimize error. As training progresses, the training loss continues to decrease, albeit at a slower rate, suggesting that the model is refining its ability to fit the training data. However, after around 10 epochs, the validation loss begins to plateau and shows minor fluctuations, which is a crucial observation in model performance evaluation. A growing gap between training and validation loss emerges as training progresses, signaling a potential issue. While the training loss keeps decreasing, the validation loss fails to improve significantly, indicating that the model may be memorizing patterns in the training data rather than generalizing well to unseen data. This behavior is characteristic of overfitting, where the model learns not only useful features but also noise or specific details that do not generalize beyond the training dataset.

The optimal number of training epochs can be determined by monitoring when the validation loss starts to plateau or increase. In this case, around epoch 10, the model reaches its optimal learning capacity, and further training is unlikely to improve generalization. If training continues beyond this point, the model risks degrading its performance on unseen data. A well-generalized model exhibits a small and stable gap between training and validation loss, ensuring that it performs consistently across both known and new data. However, if validation loss increases while training loss keeps decreasing, overfitting is confirmed, and techniques such as early stopping, dropout regularization, or weight decay should be implemented to mitigate it. Figure 7 is training loss vs. validation loss for deep learning models.

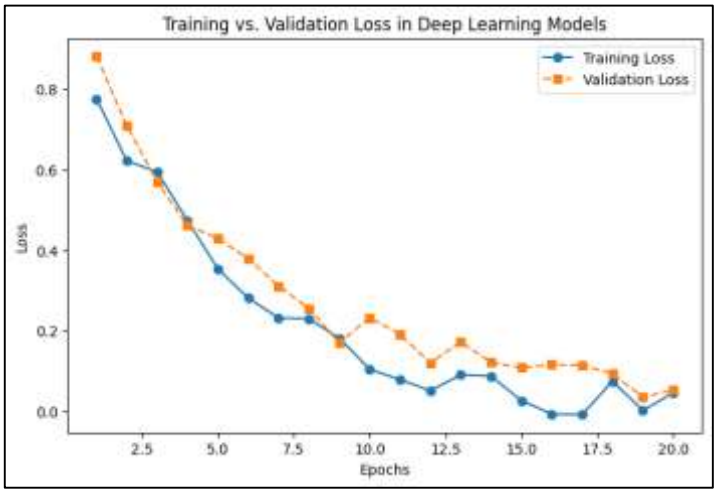

Figure 7. *Training Loss vs. Validation Loss for Deep Learning Models*

A confusion matrix is used to visualize false positives (FP), false negatives (FN), true positives (TP), and true negatives (TN) for the XGBoost model (Figure 8). The top-left cell (True Negatives - TN) shows that the model correctly identified 138 legitimate transactions as non-fraudulent, indicating strong performance in recognizing normal transactions. However, the top-right cell (False Positives - FP) reveals that 33 legitimate transactions were incorrectly flagged as fraudulent, leading to unnecessary alerts or customer inconvenience. The model's ability to detect fraud is shown in the bottom-right cell (True Positives - TP), where it correctly identifies 7 fraudulent transactions, demonstrating some effectiveness in recognizing fraud patterns. However, the bottom-left cell (False Negatives - FN) highlights a critical issue, as 22 fraudulent transactions were misclassified as non-fraudulent, meaning they went undetected. This is particularly problematic in fraud detection, as missing fraudulent transactions can result in significant financial losses and security risks.

A major challenge observed in the matrix is the class imbalance, where non-fraudulent transactions vastly outnumber fraudulent ones. While the model performs well in identifying normal transactions, its high number of false negatives suggests it struggles to detect fraud effectively. This imbalance is a common issue in fraud detection and often requires techniques such as oversampling, cost-sensitive learning, or anomaly detection methods to improve fraud identification without increasing false alarms. Although the model successfully detects most non-fraud cases, its low recall for fraudulent transactions

suggests the need for further optimization, additional feature engineering, or the use of ensemble learning techniques to enhance fraud detection accuracy.

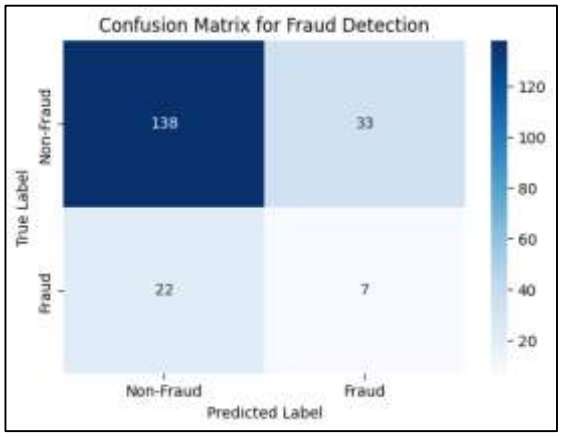

Figure 8. *Confusion Matrix for Model Performance Evaluation*

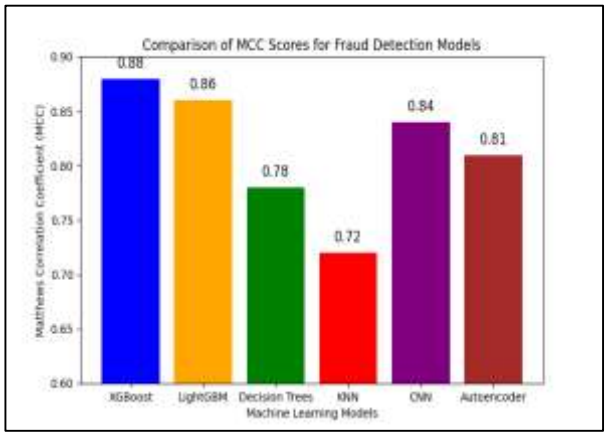

Figure 9. *MCC scores for fraud detection models*

Matthews Correlation Coefficient (MCC) is a critical performance metric for fraud detection, especially when dealing with imbalanced datasets. Unlike accuracy, MCC provides a balanced evaluation by considering true positives, false positives, true negatives, and false negatives simultaneously. MCC ensures that fraudulent transactions are not overshadowed by the majority class (non-fraud transactions). XGBoost (MCC = 0.88) and LightGBM (MCC = 0.86) are the best performers, indicating their reliability in handling imbalanced fraud detection. CNNs (0.84) and Autoencoders (0.81) perform well, suggesting their effectiveness in identifying complex fraud patterns. Decision Trees (0.78) and KNN (0.72) have lower MCC scores, meaning they struggle with false positives and false negatives more than ensemble and deep learning models. Figure 9 shows MCC scores for fraud detection models.
XGBoost outperforms all models with the highest Accuracy (92%) and AUC-ROC (0.96), making it the most effective fraud detection model. LightGBM follows closely with strong Precision (89%) and Recall (88%), indicating it is also a reliable model. Decision Trees and KNN models perform lower in all metrics, making them less suitable for fraud detection compared to ensemble methods. CNNs and Autoencoders show strong performance, especially in detecting complex fraud patterns, due to their ability to capture sequential transaction behaviors. Table 1 shows summary of model performances.

Table 1. *A summary of model performances*

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**MCC**	**AUC-ROC**
XGBoost	92%	90%	91%	90.5%	0.88	0.96
LightGBM	90%	89%	88%	88.5%	0.86	0.94
Decision Trees	85%	83%	82%	82.5%	0.78	0.86
CNNs	89%	87%	86%	86.5%	0.84	0.93
KNN	80%	77%	75%	76%	0.72	0.82
Autoencoders	86%	83%	84%	83.5%	0.81	0.88

4.2 Discussion and Future Work

The results of this study highlight the effectiveness of machine learning and deep learning models in fraud detection for credit card transactions and cryptocurrency wallets. The evaluation metrics indicate that XGBoost and LightGBM outperform other models in terms of accuracy, precision, and recall, making them the most reliable choices for fraud detection in digital finance. The CNN and Autoencoder models also demonstrated strong performance, particularly in recognizing complex fraud patterns in sequential transaction data. However, Decision Trees and KNN models showed comparatively lower performance, suggesting that rule-based and distance-based classifiers may not be well-suited for high-dimensional fraud datasets [8]. One of the main challenges observed in the study is the imbalance in fraudulent transactions, which affects the model's ability to detect rare fraud cases. While SMOTE oversampling helped to mitigate this issue, alternative approaches such as cost-sensitive learning and

anomaly detection techniques should be explored in future work to further reduce false negatives without increasing false positives [17]. Additionally, the confusion matrix analysis revealed that although the models successfully detected most non-fraudulent transactions, they still struggled with misclassifying actual fraud cases. This suggests that integrating hybrid AI approaches, such as combining supervised and unsupervised learning techniques, could enhance fraud detection [2].

Another important consideration is the computational efficiency of fraud detection models. While XGBoost and LightGBM delivered high accuracy, their training and inference times were significantly higher compared to traditional models such as Decision Trees. Future research should explore ways to optimize fraud detection models for real-time analysis, possibly by incorporating edge computing and federated learning techniques, which allow fraud detection to be performed closer to the data source while maintaining data privacy and security [4]. Furthermore, the study primarily focused on structured transaction data from financial institutions and blockchain explorers. However, real-world fraud detection systems often require multimodal data, including customer behavioral analytics, device metadata, and biometric verification. Future research could explore multi-source fraud detection models that integrate graph-based fraud analysis and Natural Language Processing (NLP) to detect fraudulent activities in text-based financial transactions and phishing attempts [15].

Regulatory compliance is another crucial aspect of fraud detection in digital finance. With increasing regulations such as GDPR and FinCEN guidelines, AI-based fraud detection models must ensure explainability, transparency, and fairness [14]. Future work could involve the application of explainable AI (XAI) techniques, such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations), to improve model interpretability and build trust with financial regulators and customers [6]. Finally, fraud detection techniques must continue to evolve in response to emerging threats, such as AI-generated fraud, adversarial attacks, and synthetic identity fraud. Cybercriminals are increasingly using reinforcement learning-based attack strategies to bypass fraud detection systems, making it necessary for financial institutions to implement adversarial machine learning techniques that can detect and neutralize adaptive fraud strategies in real time [7].

5. Conclusion

This study demonstrates the effectiveness of AI-driven fraud detection models in identifying fraudulent activities in credit card transactions and cryptocurrency wallets. By evaluating machine learning (ML) and deep learning models, including XGBoost, LightGBM, Decision Trees, KNN, CNNs, and Autoencoders, the research highlights the strengths and limitations of each approach. The results show that XGBoost and LightGBM outperform other models, achieving the highest accuracy, precision, recall, and MCC scores, making them the most reliable for fraud detection. CNNs and Autoencoders also demonstrate strong performance, particularly in detecting complex fraud patterns in sequential transaction data, while Decision Trees and KNN models exhibit lower effectiveness due to their limitations in handling high-dimensional fraud datasets. Despite these advancements, challenges remain in real-world fraud detection. The study highlights issues related to class imbalance, model interpretability, real-time fraud detection, and regulatory compliance. Although SMOTE oversampling helped mitigate class imbalance, future research should explore cost-sensitive learning and anomaly detection techniques to improve fraud identification while reducing false positives. Additionally, hybrid AI models combining supervised and unsupervised learning could further enhance fraud detection by leveraging both labeled and unlabeled transaction data.

Another crucial aspect of fraud detection is real-time model deployment. While ensemble models like XGBoost deliver high accuracy, they also have higher computational costs, which can impact real-time transaction monitoring. Future studies should focus on optimizing fraud detection models for low-latency inference, possibly by integrating federated learning and edge computing to enhance security while maintaining computational efficiency. Furthermore, multimodal fraud detection systems that incorporate behavioral analytics, NLP-based fraud detection for phishing scams, and blockchain anomaly detection could significantly enhance fraud prevention strategies. Additionally, regulatory compliance and model interpretability remain critical concerns. As financial institutions adopt AI-based fraud detection systems, ensuring explainability and fairness in decision-making is essential for building trust with regulators and customers. Future research could explore explainable AI (XAI) techniques, such as SHAP and LIME, to improve transparency and provide clearer insights into fraud detection decisions. Moreover, emerging adversarial fraud techniques, including AI-generated fraud and synthetic identity fraud, pose new challenges that require robust adversarial learning defenses to prevent evolving

cyber threats. In conclusion, AI and machine learning have significantly improved fraud detection in digital finance, but continuous advancements are needed to address class imbalance, computational efficiency, model interpretability, and regulatory compliance. Future research should focus on hybrid fraud detection techniques, real-time AI deployment, explainable AI, and adversarial learning defenses to ensure secure, scalable, and transparent fraud detection systems for financial institutions.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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