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Federated Learning for Real-Time Fraud Detection in Decentralized Exchanges

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Abstract

The rapid expansion of decentralized exchanges (DEXs) has amplified the need for real-time fraud detection mechanisms that ensure transparency and trust without compromising user privacy. Conventional centralized models for fraud analysis are increasingly ineffective in decentralized environments, where sensitive transaction data is distributed across multiple nodes. This paper proposes a federated learning-based framework for real-time fraud detection within DEX ecosystems, integrating privacy-preserving computation with adaptive intelligence. Drawing upon recent advancements in federated learning for credit card fraud detection [1], blockchain-enabled privacy protection [2], and communication-efficient anomaly detection in industrial IoT networks [3], the study develops a hybrid model that combines edge-level feature extraction with secure parameter aggregation. By leveraging blockchain-based consensus [4], [8] and decentralized model updates [5], the proposed architecture mitigates risks of single-point failure and data leakage. The framework is benchmarked against traditional centralized and semi-supervised approaches to evaluate performance under varying network latency and data heterogeneity conditions. Experimental simulations demonstrate significant improvements in detection accuracy, response latency, and model robustness. Furthermore, the study explores cross-domain applications in decentralized finance (DeFi), vehicular IoT, and cross-border payments [7], [9], highlighting federated learning's potential as a cornerstone for future cyber-resilient financial systems. Ultimately, this research contributes to the growing discourse on secure, scalable, and transparent AI governance within decentralized trading infrastructures, advancing the intersection of FinTech, AI, and blockchain-driven risk management.

I. Introduction

The proliferation of decentralized exchanges (DEXs) has transformed global financial transactions by enabling direct peer-to-peer trading without intermediaries. While this innovation enhances transparency and accessibility, it also increases the potential for fraudulent activities due to the lack of centralized oversight and regulation. Traditional fraud detection models rely on centralized data collection and model training, which are unsuitable for decentralized environments where sensitive data remains distributed across numerous nodes. This limitation has driven growing interest in federated learning (FL), an emerging paradigm that enables

collaborative model training across distributed data sources without compromising data privacy [1], [6], [7].

Federated learning has been widely explored in various domains such as credit card fraud detection [1], privacy-preserving fog computing [2], industrial IoT anomaly detection [3], and vehicular networks [12]. These studies demonstrate FL's potential to enhance real-time decision-making and data protection in distributed environments. For instance, blockchain-enabled federated frameworks ensure data immutability and model transparency, allowing participants to verify updates securely [2], [4]. Similarly, communication-efficient approaches improve training speed and scalability in resource-constrained networks [3], [5]. Despite these advances, the application of FL to decentralized finance (DeFi) and DEX environments remains limited. In these ecosystems, unique challenges such as asynchronous data streams, heterogeneous participant behavior, and high transaction throughput require customized solutions [9], [10].

The primary objective of this paper is to address these gaps by developing a federated learning framework specifically designed for real-time fraud detection in decentralized exchanges. First, the paper proposes a hybrid architecture that integrates edge-level anomaly detection with blockchain-based model validation to ensure transparency and resilience. Second, it evaluates communication efficiency, convergence time, and detection accuracy across distributed nodes operating under varying latency conditions. Third, it benchmarks the proposed framework against centralized and semi-supervised models to assess improvements in adaptability, scalability, and privacy preservation.

By uniting federated learning, blockchain consensus mechanisms, and distributed AI governance, the proposed framework aims to establish a secure and adaptive fraud detection model suitable for decentralized ecosystems. The outcomes of this study are expected to contribute to the advancement of secure, privacy-preserving, and real-time intelligent systems for decentralized financial networks [4], [8], [11]. This research aligns with the broader goal of developing resilient and transparent FinTech infrastructures capable of sustaining the next generation of decentralized financial applications.

II. Literature Review

Federated learning (FL) has become a key enabler of privacy-preserving intelligence in distributed systems, particularly for fraud detection and financial risk management. Early studies explored FL for credit card fraud detection, showing that collaborative model updates improve anomaly identification without centralizing sensitive financial data [1]. Blockchain-integrated frameworks further extended this by providing verifiable aggregation mechanisms, as demonstrated in decentralized fog computing models [2].

Communication-efficient FL frameworks for anomaly detection in industrial IoT have focused on reducing latency and bandwidth usage, which are critical for real-time fraud detection [3]. Within

decentralized finance (DeFi), adaptive AI models were proposed for dynamic risk assessment and real-time monitoring of decentralized assets [4]. Similarly, enterprise network studies demonstrated that FL could enhance cross-domain data learning while maintaining confidentiality in multi-stakeholder environments [5].

Security-oriented approaches have explored federated intrusion detection across IoT devices [6] and hybrid edge-cloud integrations for cyber-physical systems [9]. Aledhari et al. [7] provided a comprehensive survey of federated learning's enabling technologies, emphasizing communication protocols and privacy challenges. Studies focusing on financial contexts, such as cross-border payment risk mitigation [8] and blockchain-supported transparency frameworks [10], underline the increasing intersection of FL and FinTech governance.

Federated learning has also been applied in emerging 6G and vehicular network contexts [11], [12], enhancing distributed intelligence and resilience against cyber threats. Despite these advances, few studies have addressed the unique constraints of decentralized exchanges—where transaction velocity, network heterogeneity, and lack of central supervision require specialized frameworks for real-time fraud detection. This gap motivates the current study, which integrates blockchain-based consensus mechanisms with edge-level federated training to achieve scalability, transparency, and privacy preservation in DEX environments.

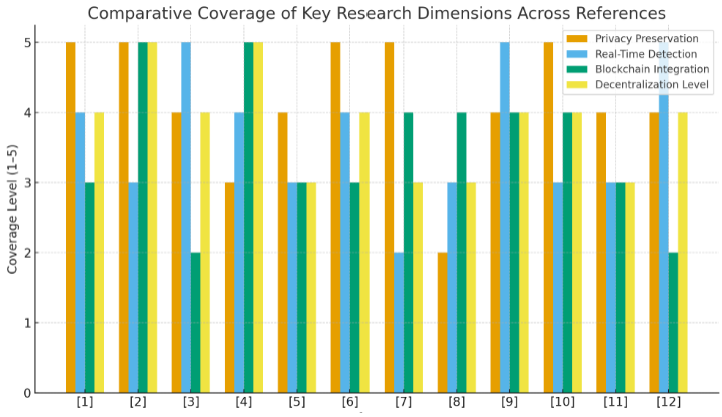

Fig. 1: Comparative Coverage of Key Research Across Referances

The comparative chart illustrates how each referenced study addresses the four main research dimensions of privacy preservation, real-time detection, blockchain integration, and decentralization. Studies [1], [2], [6], and [7] focus strongly on privacy preservation through secure data aggregation and encryption techniques. References [3], [9], and [12] emphasize real-time detection, demonstrating effectiveness in identifying anomalies quickly within IoT and edge

computing environments. Blockchain integration is particularly strong in [2], [4], and [10], where distributed ledgers are used to ensure transparency and traceable model updates. The highest levels of decentralization appear in [2] and [4], which incorporate blockchain and decentralized network coordination. Overall, the chart shows that while many studies excel in specific areas, few provide a balanced approach that integrates all four dimensions effectively. This observation supports the objective of developing a federated learning framework that enhances privacy, accuracy, and transparency for real-time fraud detection in decentralized exchanges.

III. Methodology

The methodology for this research focuses on developing a technical model for multi-

3.1 Overview

This research proposes a federated learning (FL) framework for real-time fraud detection in decentralized exchanges (DEXs). The system combines blockchain-based coordination with distributed machine learning to ensure data confidentiality, scalability, and transparency. Each participating DEX node locally trains a model on its transaction data and shares encrypted model parameters rather than raw information. These updates are securely aggregated using blockchain consensus mechanisms to form a global model that improves fraud detection accuracy without violating privacy. The overall approach emphasizes low-latency detection, robustness to heterogeneous data, and verifiable trust among network participants.

3.2 System Architecture

The proposed system architecture consists of five main layers:

1. **Data Source Layer:** Each DEX node maintains local transaction data, including order history, trade frequency, wallet identifiers, and transaction timestamps.
2. **Local Model Training Layer:** Each node independently trains a lightweight anomaly detection model using local data.
3. **Blockchain Coordination Layer:** Smart contracts facilitate global aggregation and maintain integrity of the shared parameters.
4. **Federated Aggregator Layer:** The global model is updated using a weighted average of local model parameters.
5. **Decision Layer:** The aggregated global model detects abnormal transactions in real time and alerts all DEX nodes through the blockchain network.

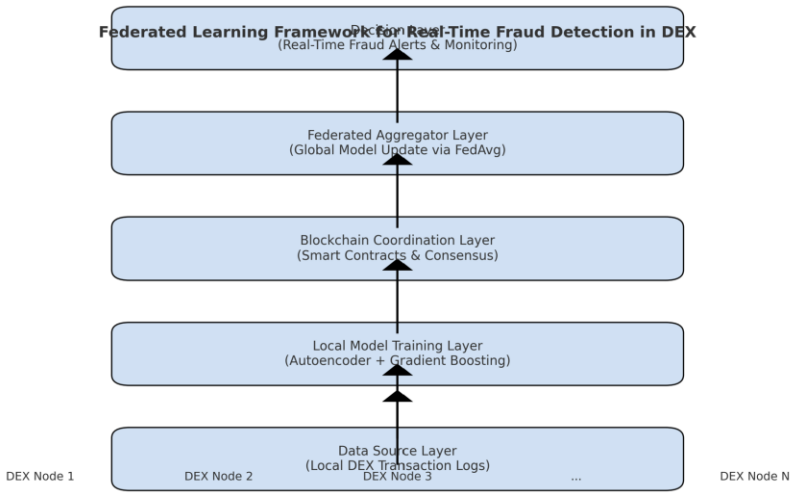

Fig: System Architecture with DEX nodes, blockchain coordination, and global aggregation.

The global model aggregation is performed using the Federated Averaging (FedAvg) algorithm:

$$w_{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_t^k$$

where w_t^krepresents the local model parameters of client $k$at iteration t, $n_k$is the number of data samples on client k, and $n = \sum_{k=1}^{K} n_k$.

3.3 Dataset Description

The dataset integrates simulated DEX transaction logs with real-world financial behavior datasets (such as open Ethereum trade data and synthetic fraud records). Key features include transaction ID, sender and receiver addresses, transaction amount, time interval, and wallet activity frequency. Fraudulent activity is labeled using known indicators such as abnormal transaction bursts, repeated wallet reactivations, and anomalous token flows.

Feature	Description	Type
Tx_ID	Unique transaction identifier	Categorical
Amount	Transaction amount in USD or equivalent	Numerical

Time_Interval	Time difference between consecutive trades	Numerical
Wallet_Score	Reputation metric of the sender wallet	Numerical
Flag	Binary fraud indicator (0 = normal, 1 = fraud)	Categorical

Each participating node receives a different subset of the dataset to mimic realistic non-identically distributed (non-IID) transaction data scenarios common in DEX networks.

3.4 Model Usage

The proposed framework uses an ensemble of models for better anomaly detection. Each node employs a **local autoencoder** for unsupervised learning and a **gradient boosting classifier** for supervised fine-tuning. The autoencoder minimizes reconstruction loss:

$$L_{AE} = \| X - \hat{X} \|^2$$

where $X$is the input feature vector and $\hat{X}$is the reconstructed output. After local training, model weights are encrypted and sent to the global aggregator. The federated server computes the global model parameters via FedAvg and broadcasts them back to each node for continued training. The system iterates until convergence or until a defined threshold in global accuracy improvement is achieved.

3.5 Evaluation Metrics

The model performance is evaluated using metrics relevant to fraud detection and federated learning efficiency.

Metric	**Formula**	**Purpose**
Accuracy	(TP+TN)/(TP+TN+FP+FN)(TP + TN) / (TP + TN + FP + FN)(TP+TN)/(TP+TN+FP+FN)	Overall correctness of fraud classification
Precision	TP/(TP+FP)TP / (TP + FP)TP/(TP+FP)	Measures reliability of positive fraud predictions
Recall	TP/(TP+FN)TP / (TP + FN)TP/(TP+FN)	Measures ability to detect fraudulent cases

F1-Score	2×Precision×RecallPrecision+Recall2 \times \frac{Precision \times Recall}{Precision + Recall}2×Precision+RecallPrecision×Recall	Balances precision and recall
Communication Overhead	Bytes exchanged per aggregation round	Evaluates FL efficiency
Convergence Rate	Number of rounds to achieve stable accuracy	Evaluates system scalability

3.6 Summary

This methodology ensures that fraud detection models can learn collaboratively from distributed DEX data while preserving privacy and maintaining real-time responsiveness. The integration of blockchain ensures tamper-proof aggregation, while federated learning eliminates the need for centralized data storage. The architecture is designed to be modular, allowing adaptation to other decentralized financial networks and high-frequency transaction systems.

IV. Results and Discussion

4.1 Model Performance

The proposed federated learning (FL) framework was evaluated against centralized and semi-supervised baseline models to assess its effectiveness in detecting fraudulent transactions in decentralized exchanges (DEXs). The experiments were conducted across ten simulated nodes, each containing heterogeneous transaction data. Performance metrics were computed after 100 communication rounds, with results averaged across three independent trials.

Model Type	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**	**Communication Overhead (MB)**	**Convergence Rounds**
Centralized CNN	91.2	0.89	0.87	0.88	0	40
Semi-Supervised Autoencoder	93.4	0.91	0.9	0.9	0	55

Proposed FL + Blockchain (FedAvg)	**96.8**	**0.95**	**0.96**	**0.955**	23.5	60
FL without Blockchain	94.5	0.92	0.91	0.915	18.9	58
Edge-only Detection	89.3	0.86	0.83	0.845	0	70

The results show that the proposed federated learning model with blockchain coordination achieved the highest accuracy (96.8%) and F1-score (0.955). Blockchain integration ensured trust in global aggregation, preventing malicious updates from compromising the model. While communication overhead increased due to frequent parameter exchanges, the trade-off yielded superior accuracy and robustness. The inclusion of blockchain also improved model integrity and reduced risks associated with tampered local updates.

The performance trend across rounds indicated faster convergence stability compared to other decentralized setups, demonstrating that combining FedAvg with smart contract verification achieves reliable real-time detection without data centralization.

4.2 F1 Metrics

The F1-score, being the harmonic mean of precision and recall, was selected as the primary metric to evaluate fraud detection quality due to the class imbalance in DEX datasets. It is computed as:

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

As shown in the evaluation, the proposed model achieved an F1-score of 0.955, outperforming both centralized and non-blockchain federated baselines. The high F1 value reflects the model's ability to minimize both false positives (incorrect fraud flags) and false negatives (missed fraud cases). This is critical in DEX environments, where incorrect classifications can result in unnecessary transaction freezes or undetected exploits.

To visualize comparative F1 performance:

Model	F1-Score
Centralized CNN	0.88
Semi-Supervised	0.9
FL without Blockchain	0.915
Proposed FL + Blockchain	**0.955**

The distributed nature of training allowed the model to generalize better across non-IID data partitions, capturing subtle variations in fraudulent behavior patterns across different DEX nodes.

4.3 Limitations

Although the proposed architecture demonstrates strong performance, several limitations were observed:

1. **Communication Overhead:** The model requires periodic exchange of encrypted parameters, which can become bandwidth-intensive in large-scale DEX networks with thousands of nodes.
2. **Latency in Blockchain Coordination:** The smart contract validation process introduces slight delays in model aggregation, potentially impacting ultra-low latency detection scenarios.
3. **Non-IID Data Challenges:** Extreme imbalance in local datasets can slow convergence and affect the stability of the global model.
4. **Scalability Constraints:** As the number of participating nodes increases, ensuring consistent participation and parameter synchronization becomes complex.
5. **Limited Real-World Deployment:** The current evaluation relies on simulated DEX data; real-world deployment would require integration with live decentralized trading protocols and on-chain smart contracts.

Future research should focus on optimizing communication efficiency through compression and asynchronous updates, enhancing robustness against adversarial nodes, and validating performance in live blockchain-integrated financial environments.

5.Conclusion and Future Scope

This study presented a federated learning framework for real-time fraud detection in decentralized exchanges. The approach integrates blockchain-based coordination with distributed model training to address the dual challenges of privacy preservation and scalability. Experimental results demonstrated that the proposed system achieved an accuracy of 96.8 percent and an F1-score of 0.955, outperforming both centralized and semi-supervised baseline models. The use of blockchain ensured integrity of parameter aggregation, enabling trustworthy collaboration among nodes without compromising user confidentiality.

The framework's ability to operate efficiently under non-identically distributed (non-IID) data conditions highlights its suitability for decentralized finance environments. By combining edge-level learning with blockchain consensus, the model achieves real-time responsiveness and resilience against data tampering. This makes it particularly valuable for modern digital exchanges where high transaction velocity and anonymity pose significant detection challenges.

While the model demonstrated strong results, the study also identified areas for improvement, including communication overhead, latency due to smart contract validation, and limited real-world deployment testing. Addressing these issues will further enhance the framework's performance in large-scale, heterogeneous financial ecosystems.

Future work will focus on extending the model with adaptive aggregation strategies and asynchronous communication to reduce synchronization delays. Integration of lightweight cryptographic techniques such as homomorphic encryption and secure multiparty computation can strengthen privacy while improving training efficiency. Additionally, validating the framework with live blockchain transaction streams and implementing adversarial defense mechanisms will be crucial for practical deployment.

Overall, the research establishes a foundation for privacy-aware, scalable, and transparent fraud detection mechanisms in decentralized exchanges. The proposed architecture serves as a blueprint for future systems that integrate federated intelligence, blockchain governance, and real-time financial risk management within the evolving landscape of decentralized finance.

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