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*Original Article*

# Real-Time Fraud Detection Using Graph Neural Networks and Federated Learning

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***Abstract -*** *Fraud continues to be one of the most pressing threats to financial systems, costing banks and consumers billions annually. Traditional fraud detection methods rely heavily on rule-based engines and static anomaly detection, which struggle against adaptive adversaries and organized fraud rings. This paper introduces a hybrid framework that leverages Graph Neural Networks (GNNs) for relational fraud detection and Federated Learning (FL) for privacy-preserving model collaboration across financial institutions. GNNs enable the identification of hidden connections between accounts, devices, and transactions that traditional models often overlook, making them highly effective against collusive schemes. Federated learning allows institutions to train models jointly without exposing sensitive customer data, aligning with privacy and regulatory requirements such as GDPR and CCPA. We present a reference architecture for federated GNN-based fraud detection, with components for local graph construction, secure aggregation, and global model dissemination. Case studies demonstrate improvements in fraud detection accuracy, reductions in false negatives, and enhanced resilience to evolving attack patterns. Challenges such as communication overhead, interpretability of GNN decisions, and cross-border regulatory acceptance are discussed. We also highlight future research directions, including quantum-accelerated graph learning and generative adversarial fraud simulations. Our findings suggest that the combination of GNNs and FL is a transformative step in building real-time, scalable, and secure fraud detection systems for global banking.*

***Keywords*** *- Fraud Detection, Graph Neural Networks, Federated Learning, AI, Banking, Privacy, Cybersecurity, Real-Time Systems, GDPR, Anomaly Detection.*

## 1. Introduction

Fraud in financial services has evolved from isolated credit card thefts to complex, organized fraud rings operating globally. The increasing digitalization of payments, combined with real-time settlement systems, has made fraud detection both critical and more difficult. Legacy systems often generate excessive false positives, frustrating customers and overwhelming analysts. AI-driven methods, particularly graph-based learning, provide an avenue to analyze the relationships between entities rather than treating them in isolation.

## 2. Background and Related Work

Graph neural networks have revolutionized tasks such as social network analysis and molecular prediction by modeling relational structures. In fraud detection, this capability allows for the identification of fraud rings spanning multiple accounts and devices. Federated learning, introduced by Google, enables collaborative training across decentralized data sources. Recent studies demonstrate the synergy between GNNs and FL, offering strong fraud detection performance while preserving privacy.

## 3. Architecture of GNN + Federated Learning Fraud Detection

The proposed architecture has three layers: (1) Local Data Processing – banks build transaction graphs locally, capturing relationships between accounts, cards, IP addresses, and devices. (2) GNN Model Training – each institution trains a fraud detection model on its local graph. (3) Federated Aggregation – secure aggregation protocols combine model updates into a global model without sharing raw data. This design balances performance with privacy preservation, making it well-suited for regulated financial environments.

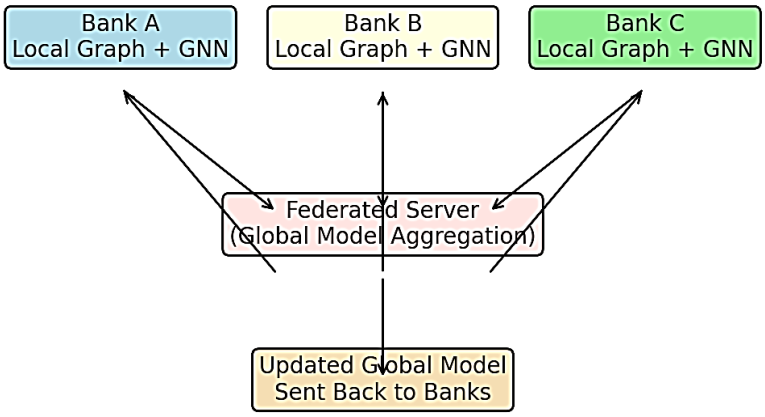


**Fig 1: Federated GNN-Based Fraud Detection Framework**

## 4. Case Studies

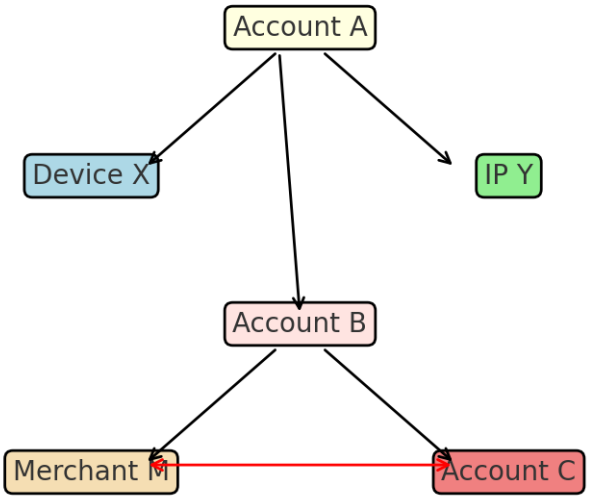


**Fig 2: Example of Fraud Ring Detected in a Transaction Graph**

- **Case Study 1**: A consortium of regional banks collaboratively trained a federated GNN, improving mule account detection rates by 30% without data sharing. Case Study 2: A global payments provider applied GNNs to cross-device transaction graphs, reducing false negatives by 22% while maintaining customer privacy. Case Study 3: An Asian digital bank deployed federated GNN fraud detection across subsidiaries, enhancing resilience to cross-border fraud attempts.

## 5. Challenges

Challenges remain in deploying GNN + FL systems at scale. Communication overhead during federated aggregation can slow convergence. Interpretability is another hurdle; regulators require explainable models, yet GNNs are often black boxes. Cross-border collaboration introduces regulatory complexity, with varying data localization laws affecting adoption.

## 6. Future Directions

Emerging technologies promise to address current challenges. Quantum-assisted GNNs could dramatically speed up graph computations. Generative AI could simulate fraud patterns, enabling proactive defense strategies. Blockchain-based logging could provide immutable audit trails for fraud detection processes. Federated learning frameworks are also evolving to handle heterogeneous data distributions, making them more practical for diverse banking systems.

## 7. Conclusion

The integration of graph neural networks and federated learning presents a powerful new paradigm for fraud detection. By analyzing relational structures and enabling collaborative training without compromising privacy, this approach enhances detection rates, reduces false positives, and aligns with regulatory requirements. Cloud-native deployments of federated GNN frameworks represent a path forward for real-time, scalable, and secure fraud detection in global finance.

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