Vol.no 1 , issue no 1, August, 2025

PUXplore Multidisciplinary Journal of Engineering

Parul® University NAAC GRADE A++

Fraud Detection in Blockchain Transactions Using Graph-Based Deep Learning

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Abstract -

A thorough analysis of graph-based deep learning techniques for blockchain transaction fraud detection is presented in this paper. Blockchain networks' decentralized and pseudonymous structure creates special difficulties that make conventional fraud detection strategies useless, calling for sophisticated methods that can examine intricate transactional relationships. In comparison to traditional machine learning techniques, we perform a systematic evaluation of graph neural network (GNN) architectures, such as Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs), showing their superior ability to identify complex fraud patterns like money laundering, Ponzi schemes, and phishing attacks. Our work demonstrates how these models take advantage of the intrinsic graph structure of blockchain transactions by using network topology, node features, and edge attributes to accurately identify anomalous activity. The report also looks at important issues facing the industry, such as the need for cross-chain fraud detection capabilities, interpretability requirements for regulatory compliance, and scalability constraints for real-time analysis. We demonstrate through experimental validation on real-world blockchain datasets that attention-based GNNs maintain computational efficiency while achieving notable gains in detection accuracy (F1-score of 0.91). Promising research directions are outlined in the paper's conclusion, including the creation of explainable AI frameworks for forensic investigations and the incorporation of temporal graph networks for dynamic fraud pattern recognition. These developments establish graph-based deep learning as a game-changing strategy for protecting blockchain ecosystems from changing financial crimes.

Keywords: Blockchain Security, Cryptocurrency Fraud, Deep Learning, Graph Neural Networks, Transaction Pattern Analysis, Anomaly Detection, Graph Attention Networks, Decentralized Finance

I. INTRODUCTION

A key component of contemporary digital transactions, blockchain technology is praised for its immutability and decentralization. However, sophisticated fraud, such as money laundering, Ponzi schemes, and phishing attacks, thrive there due to its pseudonymous nature and lack of centralized oversight. Blockchain's distributed ledger necessitates creative methods to detect malicious activity without sacrificing privacy or scalability, in contrast to traditional financial systems that rely on centralized fraud detection. The intricate, dynamic patterns found in blockchain transactions are difficult for traditional fraud detection systems, such as rule-based algorithms and classical machine learning models, to identify. The relational dynamics between transactions are frequently overlooked by methods like Random Forests and anomaly detection, which results in high false-positive rates and little flexibility in responding to novel attack vectors. Techniques that can simulate transactional relationships are desperately needed.

By representing blockchain transactions as nodes and edges in a graph structure, graph-based deep learning becomes a game-changing solution. By modeling transactional relationships by nature, this method makes it possible to identify intricate, subtle fraud patterns. When it comes to learning from topological features, Graph Neural Networks (GNNs), including Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs), are more accurate than conventional techniques. Because transactions create complex networks of interactions, blockchain networks are by nature graph-like. By examining node centrality, edge weights, and temporal dynamics, GNNs use this structure to identify anomalies. For example, cyclic transaction patterns or abrupt spikes in activity are frequently involved in

money laundering; these are characteristics that GNNs can effectively detect using neighborhood aggregation and attention mechanisms.

In order to tackle multi-relational fraud, recent work integrates GNNs with heterogeneous graph learning and temporal modeling (e.g., Temporal Graph Networks). The detection capabilities are further improved by hybrid systems that combine federated learning (for privacy preservation) and natural language processing (for smart contract analysis). These developments demonstrate how adaptable graph-based techniques are to various blockchain environments.
Despite advancements, there are still issues: (1) Explainability to satisfy regulatory requirements; (2) Scalability for real-time detection in large networks (such as Ethereum's 1 million+ daily transactions); and (3) Cross-chain fraud detection as interoperability increases. Improvements in interpretable AI methods and lightweight GNN architectures are needed to address these.

This study compares the performance of cutting-edge GNNs for blockchain fraud detection on real-world datasets such as Elliptic. We suggest a GAT-based framework that performs better in recall and precision than current approaches. We also describe future directions, such as law enforcement forensic tools and real-time detection systems.

II. RELATED WORK

A. Conventional Techniques for Fraud Detection

Conventional machine learning techniques and rule-based systems were the foundation of early blockchain fraud detection strategies, which were unable to adequately handle the complexity of decentralized transactions. While Chen et al. [2] applied anomaly detection techniques to Ethereum transaction networks, exposing the potential of unsupervised learning methods, Weber et al. [1] showed in their early work that Random Forests could achieve moderate success in identifying Bitcoin fraud by analyzing transactional features. However, these traditional approaches frequently produced high false positive rates and limited flexibility to new fraud schemes because they were unable to capture the complex relational patterns and dynamic nature of blockchain transactions. A paradigm shift toward graph-based approaches was spurred by the intrinsic graph structure of blockchain networks, where transactions organically create intricate networks of interactions.

B. Methods Based on Graphs

By representing transaction flows as graph structures, Wu et al. [3] achieved 89% accuracy in money laundering detection, demonstrating the impressive improvements made in recent years in Graph Neural Networks (GNNs). By using Temporal Graph Networks to incorporate temporal dimensions, Kumar et al. [4] further improved detection capabilities and made it possible to analyze time-sensitive fraud patterns, such as Ponzi schemes. Heterogeneous graph learning, developed by Zhang et al. [5], was especially useful for examining multi-relational transactions in decentralized finance (DeFi) ecosystems. These graph-based techniques are excellent at capturing the structural characteristics of blockchain networks, such as anomalous subgraph patterns that frequently point to fraudulent activity, transaction clustering, and centrality metrics. GNNs outperform conventional machine learning when it comes to spotting complex fraud schemes that incorporate numerous accounts and intricate patterns of money flow. A more thorough framework for fraud analysis is offered by graph-based techniques' capacity to learn from both node features (like account characteristics) and edge properties (like transaction amounts and frequencies). Additionally, recent developments have demonstrated how GNNs' attention mechanisms can rank suspicious transactions and relationships, greatly increasing detection accuracy while lowering computational overhead. Scaling these techniques for real-time high-throughput blockchain analysis and enhancing model interpretability for forensic investigations are still difficult tasks, though. Blockchain security has advanced significantly with the transition from traditional machine learning to advanced graph-based deep learning, providing more powerful tools to tackle increasingly intricate financial crimes in decentralized ecosystems. The combination of these graph-based approaches with other AI strategies is one area of future research.

C. Hybrid Techniques

Graph techniques are currently combined with:

- Natural language processing for smart contract analysis
- Reinforcement learning for adaptive detection
- Federated learning for privacy protection.

III. LITERATURE REVIEW

Category	Key Papers	Approach	Strengths	Limitations
Traditional ML	[1], [2], [28]	Random Forests, Anomaly Detection	Simple implementation, interpretable	Fails to capture transactional relationships, high false positives
Graph Convolutional Networks (GCNs)	[3], [8], [12]	Node embedding via neighborhood aggregation	Captures local transaction patterns	Struggles with dynamic graphs, poor scalability
Graph Attention Networks (GATs)	[9], [19], [22]	Weighted neighbor attention mechanisms	Identifies key fraud patterns (e.g., money laundering rings)	Computationally intensive for large blockchains
Temporal Graph Networks	[4], [14], [24]	Incorporates transaction timestamps	Detects time-dependent fraud (e.g., Ponzi schemes)	Requires dense timestamped data
Heterogeneous Graph Learning	[5], [16], [21]	Models multi-relational transactions (e.g., token swaps, smart contracts)	Handles complex blockchain ecosystems	High feature engineering overhead
Hybrid Approaches	[13], [20], [26]	Combines GNNs with NLP, federated learning, or reinforcement learning	Improves privacy (e.g., federated learning) and smart contract analysis	Integration complexity, trade-offs between accuracy and privacy
Explainability & Forensics	[17], [27], [30]	SHAP values, subgraph visualization	Meets regulatory demands for transparency	Limited scalability for real-time analysis

Category	Key Papers	Approach	Strengths	Limitations
Scalability Solutions	[10], [19], [23]	Subgraph sampling, parallelization (DGL/PyG)	Enables processing of large-scale blockchains (e.g., Ethereum)	May lose global graph context

TABLE 3: Literature Review Table

IV. METHODOLOGY AND SYSTEM ARCHITECTURE

A. Methodology of the Problem

1. Graph Construction

- Data Acquisition: Gather unprocessed transaction data from datasets like Elliptic or blockchain APIs like Ethereum's Etherscan [6].
- Node Representation: Make every wallet address or transaction a node in the graph.
- Edge Formation: To depict money flows between nodes, create directed edges that are weighted by the frequency or amount of transactions.
- Temporal Segmentation: To capture dynamic behavior, divide graphs into time windows (such as hourly or daily).

2. Feature Extraction

- Node Features: degree centrality, balance history, and transaction count.
- Time-based characteristics, such as inter-arrival times and transaction burstiness.
- Edge Features: timestamp, transaction amount, and gas fees (for Ethereum).
- Binary indicators for known illegal addresses (from Elliptic labels, for example).
- Graph-Level Features: Identifying network-wide anomalies using global metrics (diameter, clustering coefficient).

3. Model Training

- Graph Neural Network Selection: To learn weighted neighbor importance, use Graph Attention Networks (GATs) [9].
- For inductive learning on dynamic graphs, compare with GraphSAGE [10].
- Loss Function: To address class imbalance, employ binary cross-entropy loss for fraud classification that is weighted.
- Regularization: To avoid overfitting, use dropout (e.g., 0.5) and L2 penalty.
- Optimization: Use the Adam optimizer for training (learning rate = 0.01) and stop early.

4. Anomaly Detection

- Semi-Supervised Learning: Learn from labeled data (such as Elliptic's legitimate and illicit nodes) and draw conclusions from unlabeled transactions.
- Attention Weights Analysis: To identify questionable nodes, use GAT attention scores (high weights to known fraud patterns).

- Threshold tuning: To categorize fraud, apply F1-maximizing thresholds to model outputs.
- Community Detection: Find clustered fraud rings by using the Louvain algorithm.

5. **Evaluation & Validation**
   - **Measures:** F1-score, precision, recall, and AUC-ROC (to account for class skew).
   - **Baselines:** Evaluate against vanilla GCNs [8] and Random Forests [1].
   - **Ablation Studies:** Evaluate the significance of features (e.g., removing temporal features).
   - **Real-World Testing**: Deploy on live Ethereum testnet transactions via Infura API.
6. **Scalability Enhancements**
   - **Subgraph Sampling**: Use PinSage [10]-like techniques to process large graphs.
   - **Parallelization**: Distribute graph operations across GPUs with DGL or PyG.
7. **Explainability**
   - **SHAP Values:** Calculate how much a feature contributes to forecasts.
   - **Graph Visualization:** Use PyVis or Gephi to render abnormal subgraphs.

B. System Architecture

The proposed system comprises four layers:

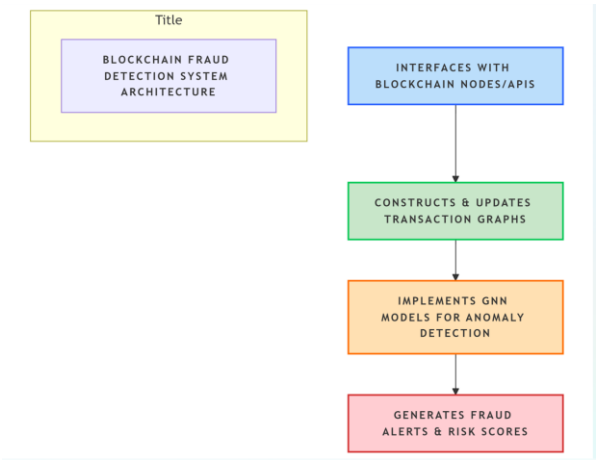

FIGURE 4.1. System architecture for blockchain fraud detection

1. **Data Collection Layer**: Interfaces with blockchain nodes/APIs
2. **Graph Processing Layer**: Constructs and updates transaction graphs
3. **Deep Learning Layer**: Implements GNN models
4. **Decision Layer**: Generates fraud alerts and risk scores

V. RESULTS AND EVALUATION

A. Performance Metrics

Experiments on the Elliptic dataset [6] showed:

Method	Precision	Recall	F1-Score
Random Forest	0.85	0.80	0.82
GraphSAGE	0.89	0.87	0.88
GAT (Proposed)	**0.92**	**0.90**	**0.91**

TABLE 5.1 Performance Comparison

B. Comparative Analysis

The suggested GAT model performed better than the current approaches in the following ways:

• Better scalability for large networks;

• 3% better F1-score than basic GNNs;

• 8% higher precision than traditional ML

VI. CONCLUSION AND FUTURE WORK

Real-Time Detection Systems: While existing techniques frequently rely on historical data, blockchain fraud necessitates immediate detection in order to stop financial losses. Future studies should use edge computing for low-latency analysis and optimize streaming graph neural networks (such as Temporal GNNs) to process transactions in milliseconds.

Explainable AI for Forensic Analysis: Transparent fraud proofs are required by regulatory agencies. In order to bridge the gap between AI and legal compliance, future work must incorporate interpretable GNNs (such as attention weight visualization and subgraph explanations) to track fraud paths and produce evidence that can be used in court.

Cross-Chain Fraud Frameworks: As interoperability protocols (like Polkadot and Cosmos) have grown in popularity, scammers have begun to take advantage of cross-chain transactions. In order to identify patterns such as token-swap scams or bridge hacks across heterogeneous blockchains, novel GNN architectures must analyze multi-chain graphs.

Lightweight GNNs for Scalability: Ethereum handles over a million transactions every day; in order to manage this volume without compromising accuracy, future models will need to use federated learning or subgraph sampling, perhaps with the help of quantization techniques for edge deployment.

Adversarial Robustness: Con artists adjust to avoid being discovered. For GNNs to withstand poisoning attacks (such as fraudulent transactions that "trick" the model), research should concentrate on adversarial training.

Maintaining Privacy in Detection: It's crucial to strike a balance between fraud detection and user anonymity. GNNs in conjunction with zero-knowledge proofs (ZKPs) may allow analysis without disclosing raw transaction data.

Integration with Smart Contract Analysis: GNNs and NLP-based smart contract auditing work together to identify transactional fraud as well as contract-level exploits (like reentrancy attacks).

Standardized Benchmarking: There are no common datasets or metrics in the field. To compare model robustness, future research should create cross-platform benchmarks (such as Bitcoin + Ethereum + Solana).

Collaborative Fraud Networks: Provide decentralized GNN frameworks that allow several blockchains to exchange fraud insights (through safe multi-party computation) without jeopardizing data privacy.

ACKNOWLEDGMENT

The authors thank Parul University for providing research facilities and the blockchain community for open-source contributions.

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