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Behavior Path Analysis for Blockchain Fraud Detection Using Graph Neural Architectures

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Abstract

With the deep penetration of blockchain technology across various fields, its security system faces severe challenges, and fraudulent activities are becoming increasingly frequent. This study focuses on the problem of fraud detection in blockchain and proposes an innovative model, FraudGNN, based on Graph Neural Networks (GNN). The model constructs a dynamic transaction graph, where transaction addresses are treated as nodes and asset transfer relationships as edges, incorporating time-series features. A Graph Attention Network (GAT) is used to extract behavioral features from node neighborhoods. In addition, a Bidirectional Long Short-Term Memory network (Bi-LSTM) is introduced to capture behavioral paths across block-level transactions, enabling accurate classification and prediction of abnormal accounts within blockchain networks. Experiments conducted on an Ethereum transaction dataset—containing approximately 3.6 million transaction records and 40,000 labeled addresses—show that the FraudGNN model significantly outperforms traditional methods such as Random Forest and Graph Convolutional Networks (GCN) in key metrics, achieving 91.2% precision, 87.5% recall, and an F1-score of 89.3%. In particular, the model demonstrates stronger generalization and reasoning capabilities when identifying previously unseen addresses, offering solid technical support for improving blockchain security systems.

Keywords

Blockchain security; Graph neural network; Behavioral path analysis; Fraud detection; Transaction graph.

1. Introduction

Blockchain technology, as an innovative paradigm based on distributed ledger systems, has attracted widespread attention since its emergence [1]. With core features such as decentralization, immutability, and traceability, it has been actively explored and applied across various domains globally [2]. In the financial sector, blockchain has significantly improved traditional cross-border payment processes. Conventional interbank remittances are limited by complex clearing procedures and the involvement of intermediaries, usually requiring 2 to 5 working days for fund settlement [3]. In addition, transaction fees typically remain high, averaging between 3% and 5%. In contrast, blockchain-based cross-border payment systems—such as Ripple's distributed network—utilize distributed ledgers and smart contracts to reduce settlement times to a few hours, or even achieve real-time transfers [4]. Meanwhile, transaction costs can be lowered to one-tenth to one-fifth of those in traditional systems. The significant improvement in fund transfer efficiency and increased

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transparency ensures that each transaction can be clearly traced throughout the blockchain network [5]. This effectively reduces both transaction risks and uncertainties.

In the field of supply chain management, the application of blockchain technology has brought transformative changes to product lifecycle tracking. Taking a well-known international luxury brand as an example, the introduction of blockchain allowed it to raise product traceability accuracy to over 99.2%. By building a blockchain-based distributed ledger, consumers can scan a code on their mobile devices to access complete information—from the origin of raw materials and manufacturing, to warehousing, logistics and final sale [6,7]. This greatly improves the transparency and reliability of product information and effectively curbs the spread of counterfeit goods in the supply chain. According to statistics, in the first year of adopting blockchain technology, the brand saw an approximate 40% year-on-year reduction in economic losses caused by counterfeit products [8]. This highlights the practical value of blockchain in supply chain management. In the healthcare sector, blockchain has created new opportunities for the management and sharing of medical data [9]. In a regional healthcare alliance project, the adoption of blockchain significantly increased data-sharing efficiency—by about 60% compared to traditional systems [10]. The average time for researchers to access patient data for scientific studies was reduced from 15 days to less than 5 days. By combining encryption techniques and distributed storage, blockchain ensures the security and privacy of patient records [11]. At the same time, smart contracts enable compliant and efficient data circulation, providing strong support for medical research, remote healthcare and other advanced applications [12]. However, as the blockchain ecosystem rapidly expands and diversifies, its security vulnerabilities have become increasingly evident. The openness and anonymity inherent in blockchain networks, while offering convenience to legitimate users, also provide opportunities for malicious actors [13]. From early double-spending attacks in the Bitcoin network to recent large-scale asset thefts caused by vulnerabilities in Ethereum smart contracts, blockchain-related fraud has evolved into more diverse and complex forms [14]. According to a report released by a recognized cybersecurity organization, blockchain fraud in 2024 resulted in global economic losses reaching USD 4.5 billion, with more than 3 million individual investors and over 5,000 corporate users affected [15]. These incidents not only cause substantial financial damage but also seriously undermine public trust and the sustainable development of blockchain technology.

Common types of blockchain fraud include fabricated transactions, address-based scams, and Ponzi schemes. These fraud activities are typically highly covert and technically sophisticated. In cases involving fake transactions, fraudsters create fictitious blockchain records and asset transfer paths to mislead users or manipulate cryptocurrency market prices [16,17]. Data from market monitoring agencies indicate that approximately 0.5% to 1% of daily transactions on major cryptocurrency platforms are suspected to be fraudulent. Address-based scams exploit the anonymity of blockchain addresses to deceive users into transferring assets to fraudulent addresses. Given the irreversible nature of blockchain transactions, victims usually find it extremely difficult to recover transferred funds [18]. Studies show that around 80% of victims in such scams are unable to retrieve their assets once the transaction is completed. Ponzi schemes remain prevalent in the blockchain domain [19]. In these cases, fraudsters lure investors with promises of high returns and use funds from new participants to pay earlier ones, thereby creating an illusion of profitability [20]. When the scheme reaches a certain scale, the perpetrators disappear with the collected funds. In the past year alone, over 200 Ponzi schemes related to blockchain were publicly reported, involving a total amount exceeding USD 1.2 billion. Traditional detection methods based on rule-matching or simple statistical analysis are increasingly ineffective in identifying such complex and dynamic fraudulent behaviors. Rule-based methods rely on predefined transaction rules and patterns, making them inflexible in adapting to rapidly evolving fraud

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strategies [21]. Simple statistical approaches can only analyze superficial features of transaction data and are unable to capture deeper relational structures or hidden behavioral patterns [22]. As a result, the development of accurate and efficient blockchain fraud detection technologies has become a critical and urgent research direction in the field of blockchain security.

In recent years, Graph Neural Networks (GNNs) have emerged as a promising technique in artificial intelligence, achieving notable progress in complex network analysis tasks [23,24]. Given the natural graph-structured characteristics of blockchain transaction data—where each transaction address can be represented as a node and asset flows as edges—GNNs are well-suited to the fraud detection needs of blockchain systems [25]. By constructing transaction graphs and applying GNNs' graph representation learning capabilities, it becomes possible to extract both node features and inter-node relationship features, thereby improving the accuracy of fraud detection [26]. Graph Attention Networks (GATs), for instance, introduce attention mechanisms that allow the model to assign different weights to neighboring nodes. This enables the network to focus on behaviorally relevant interactions, enhancing the extraction of features that are strongly correlated with fraudulent activities. Moreover, by integrating GNNs with Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks, the model can capture the temporal evolution and long-range dependencies of transaction sequences, allowing for more precise identification of fraud patterns over time [27]. Empirical studies have demonstrated that GNNs outperform traditional machine learning methods in key blockchain tasks such as anomaly detection and node classification. In a dedicated study on Ethereum, a GNN-based fraud detection model achieved a 15% to 20% improvement in precision over conventional models [28]. This study aims to investigate blockchain fraud detection methods based on Graph Neural Networks. Through innovative transaction graph construction and behavioral path analysis, we propose an efficient model named FraudGNN, and verify its effectiveness and superiority through large-scale experiments in practical application scenarios.

2. Methodology

2.1. Transaction Graph Construction

To accurately model blockchain transactions, a dynamic transaction graph with time-series characteristics is constructed. Transaction addresses—covering individuals, enterprises, and smart contract accounts—are treated as nodes. Asset transfer relationships are treated as directed edges, with the direction indicating the flow of assets from the sending address to the receiving address [29]. Since transaction timing is critical for detecting fraud-related patterns, each edge is assigned a precise timestamp. This enables the identification of abnormal behaviors, such as high-frequency operations in short time windows or rapid fund movements. Raw records are extracted from the underlying blockchain. A data parsing algorithm is applied to accurately retrieve information such as transaction addresses, transfer amounts, and timestamps. Edges are generated according to transaction records and annotated with the corresponding time information. As new transactions occur, the graph is updated in real time. This ensures that the transaction graph remains current and forms a reliable foundation for subsequent analysis.

2.2. Feature Extraction Using Graph Attention Network (GAT)

Based on the constructed dynamic transaction graph, a Graph Attention Network (GAT) is applied to deeply extract behavioral features from the neighborhood of each node. GAT employs an attention mechanism to adaptively learn the importance of neighboring nodes in

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relation to the target node. For a node i, with neighborhood N_i, the updated node representation h_i' is computed as:

$$h_i' = \sigma(\sum_{j \in N_i} \alpha_{ij} W h_j) \quad (1)$$

Here, σ denotes an activation function such as ReLU, enhancing the network's ability to capture non-linear patterns. W is a trainable weight matrix. The attention coefficient α_{ij} is computed as follows:

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k \in N_i} \exp(e_{ik})} \quad (2)$$

where $e_{ij} = \text{LeakyReLU}(a^T[Wh_i || Wh_j])$ In this expression, a^T is a learnable vector, and the LeakyReLU activation function is adopted to address the gradient vanishing issue on the negative half-axis of ReLU. After 50 training epochs, the validation loss converged to around 0.3, indicating that the GAT model could effectively assign attention weights. Analysis shows that when the transaction frequency in a node's neighborhood exceeds twice the average and there are abnormal fund fluctuations, the likelihood of the target node being fraudulent increases by approximately 30%.

2.3. Capturing Behavioral Paths Using Bidirectional LSTM

The node feature sequence extracted by GAT is fed into a Bidirectional Long Short-Term Memory (Bi-LSTM) network to capture behavioral paths along transaction chains across multiple blocks. The Bi-LSTM processes the time-series data in both forward and backward directions, allowing it to fully capture long-range dependencies. Given an input sequence

$$X = [x_1, x_2, \cdots, x_T], \quad (3)$$

the forward and backward hidden states are computed as:

$$\vec{h}_t = \overrightarrow{\text{LSTM}}(\vec{h}_{t-1}, x_t); \ \overleftarrow{h}_t = \overleftarrow{\text{LSTM}}(\overleftarrow{h}_{t+1}, x_t) \quad (4)$$

The final output at each time step is:

$$h_t = [\vec{h}_t; \overleftarrow{h}_t] \quad (5)$$

Analysis of transaction chain data shows that fraudulent behavior often follows a specific pattern: an initial phase of small test transactions (100–500 units of cryptocurrency over 3–5 transfers), followed by a large-scale transfer exceeding 5,000 units. The Bi-LSTM effectively captures such patterns. Compared with the unidirectional LSTM, it improves the accuracy of detecting complex behavioral paths by approximately 12%.

2.4. Classification Prediction

The features output by the Bi-LSTM are passed through a fully connected layer. A Softmax function is then applied to calculate the probability of each node being a normal or fraudulent account. The probability is computed as:

$$P(y = k|x) = \frac{e^{W_k^T x + b_k}}{\sum_{j=1}^{C} e^{W_j^T x + b_j}} \quad (6)$$

Here, $P(y = k|x)$ represents the probability that the input xxx belongs to class k; W_k and b_k denote the weight and bias of the fully connected layer; and $C = 2$ indicates binary classification of account types. During training, the Adagrad optimizer is used with a learning rate of 0.001. After 100 iterations, the model achieves a training accuracy exceeding 85%. The model learns the mapping between the transaction graph structure and fraud labels. During prediction, node classification is determined based on the output probabilities from the Softmax function. For a test set of 1,000 samples, the model processes 100 samples in

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approximately 5 seconds. This efficiency meets the requirements of fraud detection tasks that do not demand real-time response.

3. Results and Discussion

3.1. Experimental Setup

This study conducts experimental analysis based on an Ethereum transaction dataset, which contains approximately 3.6 million transaction records and 40,000 labeled addresses. The address labels are clearly categorized into two types: normal addresses and fraudulent addresses. To ensure the reliability and generalizability of the experimental results, the dataset is divided into training set (70%), validation set (15%), and test set (15%). For evaluation, three standard metrics are selected: Precision, Recall, and F1-score. The proposed model is compared with two baseline methods: Random Forest and Graph Convolutional Network (GCN).

Precision measures the proportion of predicted fraudulent accounts that are actually fraudulent. It is calculated as:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{7}$$

where TP (True Positives) is the number of addresses correctly predicted as fraudulent, and FP (False Positives) is the number of addresses incorrectly predicted as fraudulent.

Recall indicates the proportion of actual fraudulent accounts that are correctly identified by the model. The formula is:

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{8}$$

where FN (False Negatives) is the number of fraudulent accounts incorrectly classified as normal.

F1-score is a harmonic mean that balances Precision and Recall. It is calculated as:

$$\text{F1} - \text{score} = \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \tag{9}$$

3.2. Experimental Results

The performance of each model on both the test set and the scenario involving previously unseen addresses is summarized in the table below:

Table 1: Performance comparison of different models on the test set and the unseen address scenario

Model Type	Precision (Test Set)	Recall (Test Set)	F1 Score (Test Set)	Precision (Unseen Addresses)	Recall (Unseen Addresses)	F1 Score (Unseen Addresses)
FraudGNN	91.2%	87.5%	89.3%	88.5%	84.3%	86.3%
Random Forest	78.6%	75.3%	76.9%	65.2%	62.8%	64.0%
GCN	85.4%	81.2%	83.2%	72.1%	69.4%	70.7%

The FraudGNN model achieved significantly better performance than traditional methods across all key metrics, clearly highlighting its effectiveness and superiority in blockchain fraud

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detection tasks. This experimental result also confirms that the FraudGNN model demonstrates stronger inference and generalization capabilities when applied to previously unseen addresses, enabling it to effectively identify novel types of fraudulent behavior.

3.3. Result Analysis

Ablation experiments show that both the GAT and Bidirectional LSTM modules play key roles in the FraudGNN model. When the GAT module is removed, the model's precision decreases to 82.3%, recall to 78.1%, and F1-score to 80.1%. When the Bidirectional LSTM module is removed, the precision reaches 86.7%, recall 83.0%, and F1-score 84.8%. These results clearly demonstrate that the GAT module effectively extracts neighborhood features of nodes, while the Bidirectional LSTM captures behavioral paths across block-level transaction chains. The two modules complement each other and significantly enhance the model's ability to detect fraudulent behavior. Although GNN models present certain challenges in interpretability, analyzing the attention weights computed by the GAT module allows observation of which neighborhood nodes influence the model's fraud prediction. Neighborhood nodes with high attention weights may be closely associated with fraudulent activity. Similarly, the hidden states output by the Bidirectional LSTM reflect how different positions in the transaction chain contribute to the final classification result. These internal signals offer partial interpretability of the model's decisions, which helps improve the model's transparency.

4. Conclusion

The FraudGNN model developed in this study demonstrates strong performance on the Ethereum transaction dataset. Compared with traditional methods, it shows clear advantages and outstanding inference ability when applied to scenarios involving new addresses. In practical applications, the model can be deployed on blockchain nodes or integrated into security monitoring platforms to support real-time transaction monitoring. For example, on a cryptocurrency trading platform, the model can analyze 1,000 transactions, with each 100 transactions taking approximately 5 seconds to process. This enables timely detection of abnormal behavior and provides protection for user assets. Future improvements may include exploring more efficient graph neural network architectures to reduce computational complexity, thereby increasing detection speed by 20% to 30%. In addition, incorporating visualization techniques can help improve interpretability. Combining the model with features such as smart contract code analysis and node reputation assessment is expected to further improve fraud detection performance by 10% to 15%.

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