BITCOIN ILLEGAL TRANSACTION DETECTION METHOD BASED ON GRAPH NEURAL NETWORKS

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ABSTRACT

With the popularization of blockchain technology, cryptocurrencies like Bitcoin are widely used in digital transactions. Due to Bitcoin's anonymity and decentralized nature, it is often exploited for illegal activities, disrupting normal economic and social operations. Detecting illegal Bitcoin transactions has become a critical research focus. Traditional methods such as integrated learning, address clustering, and LSTM neural networks face challenges with category imbalance and high feature dimensionality in transaction data, leading to low recognition rates and high false alarm rates. To address these issues, this paper proposes a hybrid model combining GraphSAGE and GAT, leveraging the graph structure of Bitcoin transaction networks. By integrating GAT's attention mechanism into GraphSAGE, the model effectively captures network relationships and transaction features. Experimental results demonstrate that the proposed model outperforms traditional approaches in detecting illegal Bitcoin transactions.

***Index Terms*—** graph neural network, bitcoin illicit transaction detection, deep learning

1. INTRODUCTION

Bitcoin transaction detection is a technique to identify illegal activities by analyzing transaction behavior in the Bitcoin network. In general, the anonymous and de-neutralized nature of Bitcoin makes its transaction data high-dimensional, dynamic, and category-imbalanced, making it difficult for people to analyze whether a single Bitcoin transaction is legitimate. [1]

Therefore the use of appropriate and reasonable technology will certainly help the government to combat illegal activities such as money laundering and terrorist financing. [2]In recent years, with the rapid development of artificial intelligence, Bitcoin transaction detection methods based on machine learning and deep learning have been widely used. Traditional machine learning algorithms, such as integrated learning, SVM, and logistic regression, usually rely on manually extracted features to categorize transaction data, and thus have a high dependence on feature selection and exhibit limitations for complex transaction networks. Among the deep learning algorithms, Long Short-Term Memory (LSTM) networks are able to capture the time-series characteristics of Bitcoin transactions, and Convolutional Neural Networks (CNNs) are able to perform automated feature extraction on high-dimensional data. [3]However, none of these methods can fully utilize the graph structure information in the Bitcoin transaction network. [4] In contrast, graph neural networks (GNNs) have unique advantages in processing complex graph data by modeling the graph structure of the transaction network and capturing the node relationship information, so the bitcoin transaction detection model based on graph convolutional networks (GCNs) has become a hot research topic nowadays. [5]

Bitcoin transaction detection is formulated as a pattern recognition problem, which involves two main processes: feature extraction and data classification for identification, and consists of the following modules: transaction data input, data preprocessing, feature extraction and selection, classification, and finally transaction illegitimacy identification.

The main contribution of this paper can be summarized as follows:

- A hybrid graph neural network model is proposed: This paper introduces the attention mechanism of GAT (Graph Attention Network) on top of the traditional graph neural network GraphSAGE, which is good at extracting node features by aggregating the feature information of neighboring nodes, while the attention mechanism of GAT is able to dynamically assign the weights of neighboring nodes to capture the importance of different transaction nodes in the Bitcoin transaction network more efficiently. GAT's attention mechanism can dynamically assign the weights of neighbor nodes to capture the importance of different transaction nodes in the Bitcoin transaction network more effectively. Combining the advantages of both, this paper proposes a hybrid graph neural network model.

- Solution to the data imbalance problem: Aiming at the problem of category imbalance in bitcoin transaction data, this paper introduces a weight balancing strategy

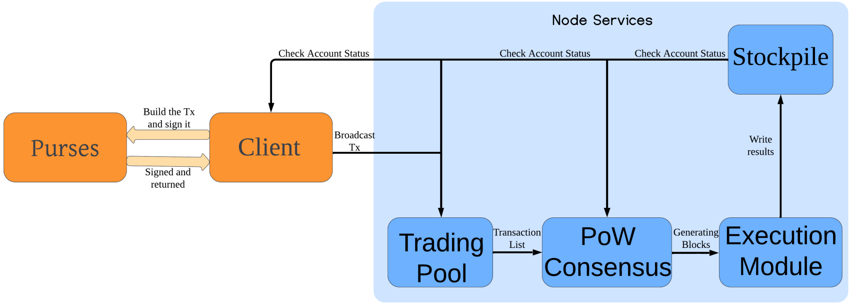

Fig. 1. Bitcoin Trading Process

during model training to reduce the impact of the imbalance of the proportion of positive and negative samples on the detection effect. In addition, the node features of the transaction network are optimized by combining the feature enhancement method to improve the sensitivity of the model to abnormal samples.

- Experimentation and evaluation: In this paper, the proposed model is validated through several experimental settings using publicly available Bitcoin transaction datasets. The experimental results show that compared with the traditional methods, the model in this paper shows significant improvement in metrics such as accuracy, F1-score, and recall, especially in the identification of illegal transaction samples, which exhibits lower false positives and misses.

This paper is organized as follows: Section 2 presents background information and previous work on bitcoin transaction detection. Section 3 details the design and implementation of the hybrid graph neural network model proposed in this paper, including data preprocessing, fusion of GraphSAGE layer and GAT layer, and construction of the classification module. The fourth section demonstrates the experimental design and result analysis, verifying the performance of this paper's model through multiple sets of experimental comparisons and comprehensively comparing it with existing methods. Finally, section 5 summarizes the conclusions of this paper.

2. RELATED WORK

In this section, we give some theoretical knowledge and background information on bitcoin transaction detection.

2.1. Graph Theory

Graph theory is a branch of mathematics that focuses on the study of graphs as structures and their properties. Graphs are mathematical objects with nodes and edges that are used to describe relationships and links between objects.

A graph $G = (V, E)$ is a set composed of the following two subsets:

- V: A set of nodes, representing individual entities in the graph.
- E: A set of edges, representing the connections between nodes.

Graph theory is a discipline that analyzes the structure and dynamic behavior of graphs through core concepts such as paths, connectivity, and degree.

2.2. Bitcoin Trading Process

The Figure1 above is a sketch of the flow of a Bitcoin transaction, revealing the public key encryption and digital signatures to achieve security and transfer of ownership during a Bitcoin transaction. The construction and signing of a Bitcoin transaction is done by the client based on the function of the transaction (e.g., transferring money or invoking a contract), including information about the sender, receiver, and transfer amount. As it relates to the security of personal assets, the blockchain system requires transaction integrity and data security. The transaction is signed through the wallet using a private key and sent to the node's transaction pool. The transaction pool verifies the correctness and legitimacy of the transaction; illegitimate transactions are eliminated and legitimate transactions are retained in the pool, waiting to be processed by the consensus module. When the consensus module reaches an agreement, the transactions to be processed are selected from the transaction pool and packaged into blocks, and handed over to the execution module to complete the logic submitted by the user. After the execution is completed, the transaction results and block information are recorded to the storage module and finally permanently saved on the blockchain, i.e., a transaction is completed.

Through the above theoretical analysis, it is not difficult to find that each transaction can be modeled as a node in the graph, and each transaction involves a sender and a receiver, and is connected to the blockchain through transaction pools and blocks, so the Bitcoin transaction process presents a natural graph structure.

2.3. GNN

Graph Neural Network (GNN) is an extension of deep learning for processing graph-structured data as a neural network model that effectively captures structural information about nodes and edges in a graph as well as their characteristics. The core idea of GNN neural networks is to learn the representation of the nodes in the graph and the global graph structure through a message passing mechanism whereby each node receives information from its neighboring nodes and updates its own state. [6]

2.4. Description of The Dataset

Due to the limited amount of Bitcoin data, this paper uses a dataset from Elliptic, a company that focuses on blockchain technology and cryptocurrency analysis. The Elliptic dataset is a publicly available dataset focused on blockchain transaction analysis. The dataset consists of 49 blocks of Bitcoin transactions in the form of a directed graph representing the transaction network, where nodes represent transactions and edges represent the flow of money between transactions. The dataset contains 203,769 transaction nodes, of which 54% are legal transactions (illicit), 2% are illegal transactions (illegal), and the remaining 44% are unlabeled. Each transaction node has 166 features including local features, neighborhood features and temporal features.

3. METHODS

3.1. Data Analysis

3.1.1. Exploratory Data Analysis

In order to gain a deeper understanding of the Elliptic dataset characteristics and accurately grasp the nature of the data points, this paper conducts an exploratory analysis (EDA), which employs visualization and statistical analysis methods to comprehensively explore the data structure, distribution, and characteristics to perceive the importance of the nodes in the bitcoin transaction network as well as the difference in the structure and distribution of the data of the legitimate and illegitimate transaction nodes.

3.1.2. Exploration of Node Importance Assessment

Measuring the importance of nodes is extremely important in graph studies. In this paper, three centrality metrics, namely closeness centrality, degree centrality and mediated centrality, are used to assess the importance of nodes.

- Closeness Centrality

Closeness centrality measures the average shortest path distance from a node to all other nodes in the network. In other words, it reflects the efficiency with which information spreads from one node to all the others.

$$C(v) = \frac{1}{\sum_{u \neq v} d(u, v)}$$

where $d(u, v)$: The shortest path distance between nodes u and v.

Nodes with high closeness centrality are located at the center of the network and can efficiently access other nodes. These nodes typically have a low average distance to other nodes, enabling them to interact more effectively. A node with high closeness centrality is beneficial for communication networks, as it reduces the time or cost of information flow.

In order to better evaluate the network topology, this paper first selects the ten nodes with the highest proximity centrality and draws the local subgraph structure between the ten nodes, as shown in the figure2.

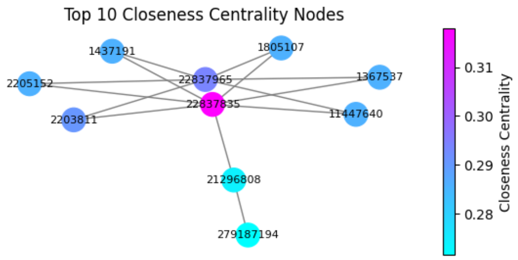

Fig. 2. Top 10 Closeness Centrality Nodes

Where the pink nodes in the graph indicate the highest proximity centrality, while the blue to cyan nodes are decreasing in order, the graph explains the distribution structure of high proximity centrality nodes in the network.

- Degree Centrality

Degree centrality measures the number of direct connections (i.e., neighbors) of a node in a network. The formula is:

$$C(v) = \frac{\deg(v)}{n - 1}$$

where $\deg(v)$ is the degree of node v (i.e., the number of edges connected to v), n is the total number of nodes in the network.

Nodes with high degree centrality indicate that the node is directly connected to many other nodes in the network. They are likely to be the most active or important nodes in the network, participating in the most interactions. Nodes with high degree centrality may represent participants in a large number of transactions, such as key traders or major addresses in cryptocurrency networks.

- Mediated Centrality

  Mediated centrality measures a node's ability to act as a "bridge" or "intermediary" in the network, indicating how frequently the node appears on the shortest paths in the network. The formula is:

$$C(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

  where $\sigma_{st}$is the total number of shortest paths between nodes s and t, $\sigma_{st}(v)$is the number of those shortest paths that pass through node v.

  Nodes with high mediated centrality indicate nodes that serve as bridges or intermediaries in the network, connecting different communities or subnetworks. These nodes may represent critical hubs or key intermediaries in the network; their removal could greatly affect network connectivity. Nodes with high mediated centrality may play critical roles in financial networks, as they appear on multiple transaction paths and could be key participants or addresses.

The final graph structure(Figure3 is plotted below, where different colored labels represent transaction nodes of different levels of importance.

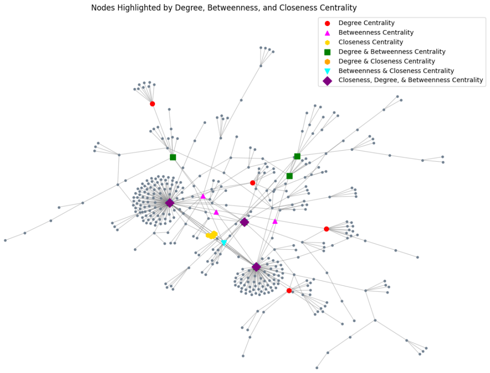
Nodes Highlighted by Degree, Betweenness, and Closeness Centrality
● Degree Centrality
▲ Betweenness Centrality
⬢ Closeness Centrality
■ Degree & Betweenness Centrality
⬢ Degree & Closeness Centrality
▼ Betweenness & Closeness Centrality
◆ Closeness, Degree, & Betweenness Centrality

Fig. 3. The distribution of nodes under different centrality

3.1.3. *Characterization of Illegal and Legal Data*

Illegal and legal data have different data characteristics, so this paper analyzes the structural characteristics and distribution differences between the two types of transaction nodes, illegal and legal, and the results obtained are shown in the figure4.

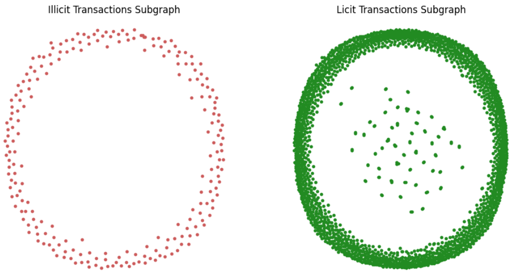

Fig. 4. Characteristics of Illegal and Legal Data

According to the analysis of the above figure, it can be seen that the node distribution of illegal transactions is sparse, with fewer network connections, usually showing a decentralized or isolated small-group structure, reflecting its covert and low-interaction characteristics, while the node distribution of legal transactions is more dense, with active network connections, and there is an obvious aggregation phenomenon in the central area, forming the core group of high-frequency transactions. This difference suggests that illicit transactions tend to reduce the likelihood of being tracked, while legitimate transactions typically engage in more complex and extensive network interactions.

3.2. Construction of Graph Neural Hybrid Network Models for GraphSAGE and GAT

3.2.1. *Algorithm Modeling*

According to the above analysis, because of the complex topology and feature extraction requirements in the Bitcoin transaction network, it is often difficult for the single graph neural networks previously studied to meet the relevant requirements. In this paper, we choose the graph neural hybrid network model that combines GraphSAGE and GAT. The neural network, which is shown in the figure5 is constructed according to the following steps.

- Data loading and pre-processing

  Based on the dataset characteristics, the data is extracted and categorized into feature data, category labels and transactional relationship data:

  - feature data $X \in \mathbb{R}^{n \times d}$
    where n is the number of transaction nodes, d is the dimensionality of the feature vector for each transaction node, $X[i,:]$ represents the feature vector of the i-th transaction node.
  - category labels $Y \in \{0, 1\}^n$
    where $Y[i] = 0$ indicates that node i is a legal transaction (*class = 1*), $Y[i] = 1$ indicates that node i is an illegal transaction (*class* = *2*).

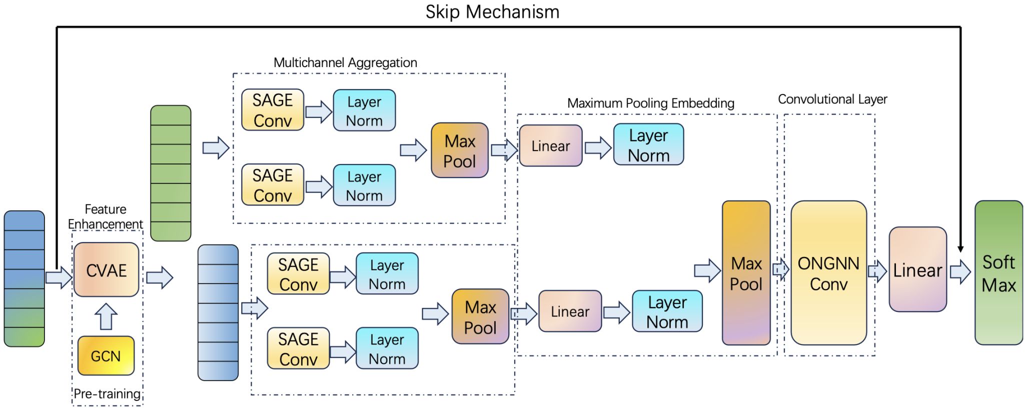

Fig. 5. GraphSAGE and GAT mixed graph neural network structure diagram

- transactional relationship data $E \in \mathbb{R}^{2\times m}$
  where, m is the number of transaction relationships (edges), $E[0,j]$ and $E[1,j]$ represent the starting node and the target node of the j-th edge, respectively.

The diagram construction process is as follows:

(1)Selecting Legal and Illegal Transaction Nodes

By selecting transaction nodes with legal classification (*class=1*) and illegal classification (*class=2*), the set of nodes is generated as:

$$V = \{v_i \mid Y[i] \in \{0,1\}, i = 1,2,\ldots,n\}$$

(2)Constructing Node Index Mapping

Transaction identifiers (*txId*) are mapped to continuous node indices:

$$\text{Map}(\textit{txId}_i) \to i, \quad i \in \{1,2,\ldots,n\}$$

(3)Constructing Edge Index Matrix

For the source and target nodes (*txId1* and *txId2*) in transaction relationships, the mapping is:

$$E = \begin{bmatrix} \text{Map}(\textit{txId1}_j) \\ \text{Map}(\textit{txId2}_j) \end{bmatrix}, \quad j = 1,2,\ldots,m$$

The edge index matrix E represents the connections between nodes in the graph.

- Residual Map Neural Network Layers

The residual graph neural network combines the features of GraphSAGE and Graph Attention Network (GAT) while using jump connections, which in turn builds a neural network model structure divided into input, hidden and output layers.

(1)Input Layer

Input:

- Node feature matrix $X \in \mathbb{R}^{n\times d}$: The initial features of each node.
- Edge index matrix $E \in \mathbb{R}^{2\times m}$: Represents the relationships between nodes.

(2)Hidden Layer

1) The first layer

In this paper, data feature extraction uses GraphSAGE as a graph convolution operator to aggregate information from node domains, convert raw node features into high-level feature structures, and perform feature analysis in the following steps:

Assume the node feature matrix is X, the edge set is E, and each node's initial feature dimension is d. The output feature dimension of the first hidden layer is h.

- Neighborhood Sampling
  For a node v, GraphSAGE randomly samples a subset of neighboring nodes $\mathcal{N}(v)$, instead of using all neighbors, to reduce computational complexity.
- Feature Aggregation
  Using an aggregation function (e.g., mean, pooling, or LSTM), the features of v's neighbors X_u are aggregated:

$$h_{\mathcal{N}(v)} = \text{Aggregate}(\{X_u \mid u \in \mathcal{N}(v)\})$$

- Feature Update

The aggregated feature $h_{\mathcal{N}(v)}$ and the node's own feature X_v are combined and transformed using a linear transformation and an activation function:

$$h_v^{(1)} = \sigma\left(W \cdot \text{Concat}(X_v, h_{\mathcal{N}(v)})\right)$$

2) The second layer

According to the incoming feature information from the first layer of GraphSAGE neural network, in order to dynamically allocate each node to assign different weights to its neighboring nodes, a graph attention network is used to introduce the attention mechanism for node weight allocation, and then to model the node importance at a fine-grained level, and the specific working mechanism is as follows:

- Calculation of Attention Coefficients

  For a node v, GAT calculates the attention coefficient α_{vu} for its neighbor node u:

  $$\alpha_{vu} = \frac{\exp(e_{vu})}{\sum_{k\in\mathcal{N}(v)} \exp(e_{vk})}$$

  where:

  $$e_{vu} = \text{LeakyReLU}\left(\mathbf{a}^\top [W\mathbf{h}_v \| W\mathbf{h}_u]\right)$$

  - e_{vu}: Attention score between node v and its neighbor u.
  - W: Linear transformation weight matrix.
  - $\mathbf{h}_v, \mathbf{h}_u$: Input features of nodes v and u, respectively.
  - $\|$: Concatenation operation.
  - $\mathbf{a}$: Learnable attention weight vector in the attention mechanism.

- Aggregation of Neighbor Features

  After computing the attention coefficients, GAT aggregates the features of neighboring nodes:

  $$\mathbf{h}'_v = \sigma\left(\sum_{u\in\mathcal{N}(v)} \alpha_{vu} W\mathbf{h}_u\right)$$

  where:
  - $\mathbf{h}'_v$: Updated feature of node v.
  - σ: Non-linear activation function (e.g., ReLU).

- Multi-Head Attention Mechanism

  To improve the robustness of the model, GAT typically uses a multi-head attention mechanism, combining the outputs of multiple attention heads:

  $$\mathbf{h}'_v = \|_{k=1}^{K} \sigma\left(\sum_{u\in\mathcal{N}(v)} \alpha_{vu}^k W^k \mathbf{h}_u\right)$$

3)Jump connection

In the process of deep network, it is easy to appear gradient disappearance and over-smoothing problem, this paper adopts the way of jump connection to connect the first layer of inputs and raw data to the subsequent layer, the specific formula is shown as follows:

The transformation through a linear layer is defined as follows:

$$Z_{\text{linear}} = W_{\text{linear}} C_{\text{conv}} + b_{\text{linear}}$$

where:

- W_{linear}: Weight matrix.
- b_{linear}: Bias term.

The output of the linear layer is processed through addition and the softmax operation, combining the input features and the transformed features to produce the final classification or regression result. This step incorporates the weight of the original input features to ensure that the final output reflects the importance of the input features.

The importance of the input features is reflected as follows:

$$\hat{y} = \arg\max\left(\text{softmax}(Z_{\text{linear}} + W_{\text{input}} X, \text{dim} = 1)\right)$$

where:

- W_{input}: Weight matrix for the input features.
- softmax: Outputs a probability distribution, used for classification or regression.
- argmax: Finds the class or value corresponding to the highest probability.

(3)Output Layer

Assume:

- The initial input features are $X \in \mathbb{R}^{N\times d}$, where N is the number of nodes, and d is the feature dimension.
- The output classification has C classes.

The mathematical flow of the output layer is as follows:

- Output of GAT

  $$X_{\text{GAT}} = \text{GAT}(X)$$

  where $X_{\text{GAT}} \in \mathbb{R}^{N\times C}$.

- Residual Connection Mapping

  $$X_{\text{residual}} = W \cdot X + b$$

  where $W \in \mathbb{R}^{C\times d}$, $b \in \mathbb{R}^C$.

- Feature Fusion

$$Z = X_{\text{GAT}} + X_{\text{residual}}$$

- Activation Function Application

$$Y = \text{LogSoftmax}(Z)$$

where $Y \in \mathbb{R}^{N \times C}$ represents the predicted probability distribution for each node.

- Regularization of the model

During the model training process, the regularization mechanism is introduced to improve the generalization ability of the model and prevent overfitting. By constraining the network weights and randomly suppressing the activities of some neurons, regularization can effectively reduce the model's dependence on the training data, thus improving the model's performance on the validation and test sets. In this paper, common regularization methods such as Dropout and Weight Decay are used.

3.2.2. Model Parameter Optimization Evaluation

The loss function can be expressed as:

$$\mathcal{L} = \mathcal{L}_{CE}$$

The cross-entropy loss function is used to measure the difference between the model predictions and the true labels. It is a common loss function in supervised learning. The cross-entropy loss function $\mathcal{L}_{CE}$ is defined as:

$$\mathcal{L}_{CE} = -\sum_{i} y_i \log(\hat{y}_i)$$

The proposed Bitcoin anomaly detection model, through feature enhancement, multi-channel aggregation, max pooling, convolutional layers, and the use of skip mechanisms, successfully addresses the challenge of detecting complex anomalies in Bitcoin transaction networks. This design not only improves detection accuracy but also demonstrates stronger robustness in representing diverse data augmentation and complex network structures.

4. EXPERIMENTS

In this paper, the dataset is split into training set, validation set and test set divided into 80%, 10% and 10%. The graph neural hybrid network models of GraphSAGE and GAT were trained and the corresponding parameter metrics were selected for analysis.

4.1. Indicator Selection

Accuracy, recall, precision, FI score and confusion matrix are selected as evaluation metrics for the unbalanced classification problem of Bitcoin data.

- Accuracy $= \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$
- Precision $= \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$
- Recall $= \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$
- $F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$
- Confusion Matrix $= \begin{bmatrix} \text{True Positives} & \text{False Positives} \\ \text{False Negatives} & \text{True Negatives} \end{bmatrix}$

4.2. Experimental Results

Based on the above analysis, the data of accuracy, precision, recall and F1-Score metrics are plotted with the number of training images as shown in figure6.

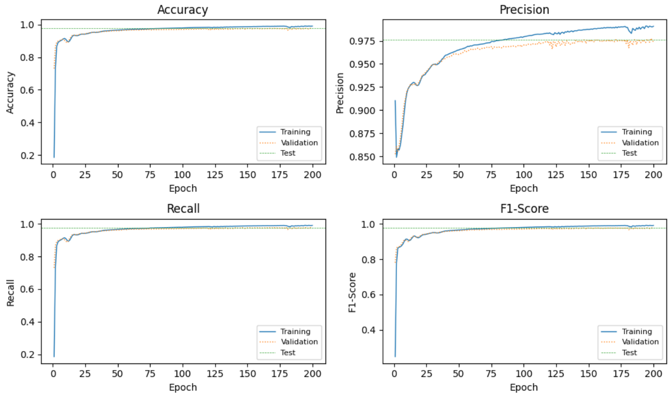

Fig. 6. Experimental Results

Analyzing the image findings, it is found that the four core metrics (Accuracy, Precision, Recall, and F1 Score) increase rapidly in the early stage of training (within about 50 iterations), and then gradually stabilize after about 100 iterations, eventually approaching 1. Meanwhile, the confusion matrix image(Figure7) is plotted.

Overall, the model performs extremely well in classifying legal transactions, but its performance in classifying illegal transactions is somewhat lacking, which may be related to the small number of illegal transaction samples. This indicates that the model has a high classification accuracy in the overall task, but there is still room for improvement in its ability to classify a few classes. The distribution of predicted probabilities of legal (Licit) and illegal (Illicit) transactions for the model out of graphical neural network (GCN) during the training and testing phases(figure8) is also plotted. The figure 8 shows that the model has a clear distribution of predicted probabilities for legal and illegal transactions and has

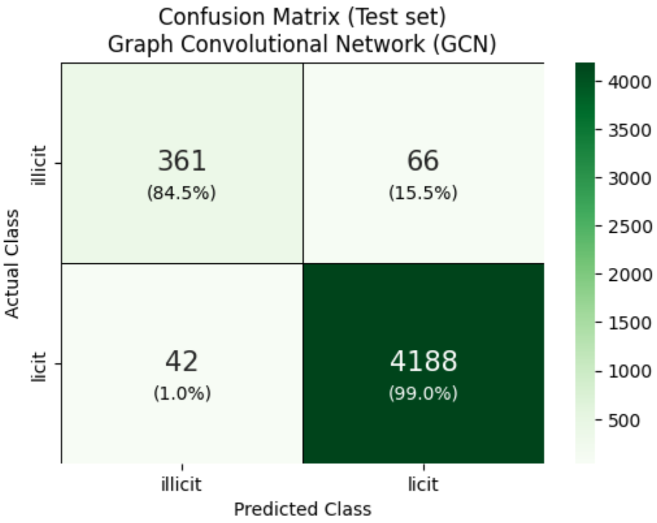

Fig. 7. Confusion Matrix

good classification ability. The probability distributions of legal and illegal transactions are almost completely separated, which reflects the high accuracy and robustness of the model in classifying transactions. In addition, the distribution curves of the training and test sets are similar, which further indicates that the model's performance on the test set is consistent with the training set and has good generalization ability.

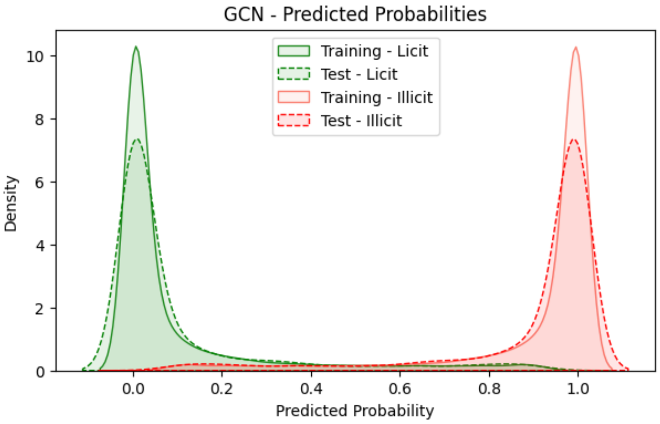

Fig. 8. Predicted Probabilities

4.3. Model Comparisons

In order to enhance the persuasive power of the experiment, the method of this paper and the traditional single model (adaboost) are compared, and a single GAT map neural network model is also selected for comparison, and the final table is obtained as follows.

Table 1. Performance Comparison

Method	Accuracy	Precision	Recall	F1
Adaboost	0.9639	0.7230	0.6527	0.6861
GAT	0.9602	0.8342	0.4843	0.6128
Proposed	**0.9791**	**0.9383**	**0.6475**	**0.7662**

The Proposed Method delivers the best results among the three models, especially in precision and F1 score. Its balanced performance makes it the most reliable choice for tasks like detecting illegal transactions in Bitcoin networks, where both minimizing false positives and capturing true positives are essential. Adaboost and GAT may still be useful in specific scenarios but are less suitable for comprehensive anomaly detection.

5. CONCLUSION AND FUTURE WORK

In this study, we have systematically analyzed and experimented with graph neural network technology for the problem of detecting illegal transactions in the Bitcoin transaction network, and achieved certain results. The exploratory analysis of the Elliptic dataset reveals the significant differences between legal and illegal transactions in terms of node features and network structure, which provides a solid foundation for the construction of graph-based deep learning models. In terms of model design, the residual network architecture combining GraphSAGE and GAT improves the feature learning capability and model training stability through the multi-head attention mechanism and jump connection. The experimental results show that the model exhibits high classification accuracy, precision, recall and F1 score in the task of illegal transaction classification, which fully validates the potential of graph neural networks in complex network data analysis.

Although this study has made some progress, there are still some limitations, which provide room for further optimization in subsequent studies. First, the problem of uneven distribution of data samples is still significant, and the number of illegal transaction samples is extremely sparse compared to legal transactions, which leads to the limited performance of the model in classifying a few classes of samples. This not only reduces the reliability of the model in real-world application scenarios, but also puts higher requirements on the generalization ability of the model. In addition, existing modeling methods are mainly based on static graph structures, failing to fully explore the dynamic evolution characteristics of the transaction network, while the Bitcoin transaction network is essentially an ever-changing dynamic system, a characteristic that may contain important patterns and laws with far-reaching significance for the detection of illegal transactions.

In summary, this study shows that graph neural networks have great potential for application in blockchain illegal transaction detection, providing strong support for the security and compliance of blockchain finance. With the growth of data scale, the improvement of model structure and the maturity of dynamic modeling technology, the illegal transaction detection method based on graph neural network will further exert its advantages and become an important tool to promote the healthy development of blockchain ecology.

6. ACKNOWLEDGEMENT

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