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Exploring the Use of Graph Neural Networks for Blockchain Transaction Analysis and Fraud Detection

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Abstract:- The digital system is increasing day by day while various organizations are facing problems during transactions and false activities. This research is investigating fraud detection in blockchain transactions-data used to focus on Ethereum_network. To implement the layers of Graph-Convolutional Networks (GCNs) that remain in the study, they convert blockchain transactional data into a graph structure with nodes representing addresses and edges representing transactions. The methodology includes data collection with preprocessing and graph representation in the implementation of GCN layers to analyze and detect deceitful activities. The outcomes illustration of the GNN model achieves a high accuracy score and precision with recall and F1-score. The analyses effectively identify fraudulent transactions while minimizing false positives. This work demonstrates the probability of GNNs to enhance fraud detection in blockchain systems and recommends future research directions convoluted in real-time data integration and advanced neural-network architectures toward advancing the toughness and effectiveness of fraud-detection mechanisms in trendy decentralized financial ecosystems.

Keywords:- *Graph Neural Networks (GNNs), Graph-Convolutional Networks (GCNs), Blockchain, Ethereum Networks.*

I. INTRODUCTION

➢ *Backgrounds Study*

The concept of blockchain has become a ground-breaking invention with significant ramifications for several sectors and companies. A distributed-system decentralized ledger system called blockchain makes it possible to track events transparently and safely. In contrast to conventional centrally managed databases for electronic ledger functions through an internet of node locations, every node keeps an exact duplicate of the ledger [1]. The blockchain system refers to a sequential sequence of securely linked operations that are grouped as chunks. These changes to a brick would need agreement from a large number of network users, guarantee permanence and openness and make it extremely resistant to manipulation and counterfeiting [2]. These foundational principles of blocking chain technology include decentralization in transparency and cryptographic security systems. Decentralization eliminates the need for intermediaries to distribute control and ownership among network participants, still reducing costs and increasing efficiency in transaction processing [3]. Transparency stems from the public nature of blockchain archives, where all transactions are visible to network participants while preserving the anonymity of individual user's cryptographic techniques. Cryptographic systems for security ensure data integrity and confidentiality using advanced encryption methods to protect sensitive information within transactions. These attributes have made blockchain technology not only a cornerstone of cryptocurrencies like Bitcoin and Ethereum but also a transformative force in sectors such as finance, supply chain management and healthcare systems. Offering blockchain continues to evolve, full of potential to foster trust in streamlining operations and permit new business models and is gradually recognized in driving innovation and adoption worldwide [3-4].

In a system for the foundational knowledge of blockchain, the paper underscores the critical significance of transaction analysis besides fraud detection inside blockchain ecosystems. It explores the inherent challenges associated with ensuring trust and safety in decentralized networks wherever anonymity and pseudonymity are prevalent [5]. The section discusses real-world instances of fraud, such as hacks, scams, and money laundering, which have underscored the necessity for robust fraud detection mechanisms in blockchain applications. Given highlights the implications of fraudulent activities on user confidence in regulatory compliances and the global integrity of blockchain-based transactions [32].

➢ *Introduction to Graph Neural Networks-(GNNs)*

Graphs represent a powerful lesson in machine learning, specifically near-grip statistics that can be represented as graphs. A graph consists of nodes (vertices) that are interconnected via edges (links or relationships). GNNs are mainly effective for tasks connecting relational data, for understanding the relationships between entities is crucial for making accurate predictions or else classifications [6].

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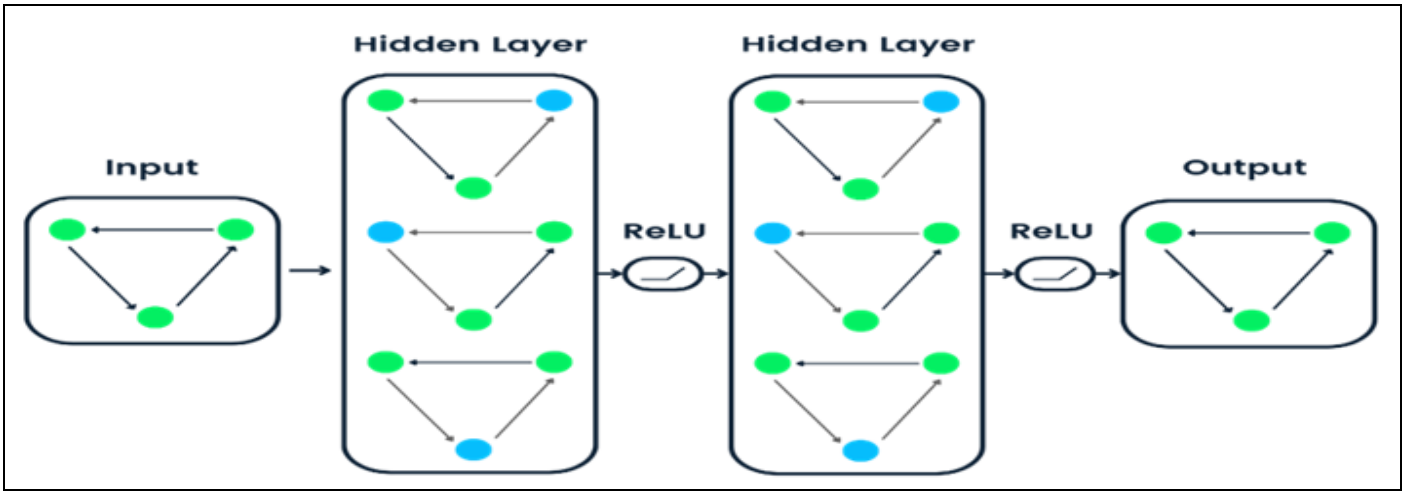

Fig 1 GNN Graph Structure [6-7]

➢ *Maintaining the Integrity of the Specifications*

- *Input Representation:*

While inputting the info of Apiece nodes in the graph, it remains associated with early feature vectors that encapsulate information about the node. This could include attributes such as transaction details in blocks-chain and node features in a social network or molecular properties in chemistry.

- *Hidden Layers:*

They typically consist of multiple layers, and each layer refines the representation of nodes based on their neighborhood relationships. The third hidden layer computes new node representations to aggregate information from neighboring nodes.

- *ReLU Activation Function:*

After hidden to employed of Rectified-Linears-Units function is (ReLU) activations fun σ(x)=max ⁡(0,X/)\sigma(x) = \max(0, X)σ(x)=max(0,X) is commonly used in GNNs [7]. It introduces a non-linearity system and helps the networks learn intricate patterns in the information. Applying the ReLU weighted sum ensures that only positive activations are propagated to the next layers, enhancing the network's ability to model difficult relationships.

- *Output Layer:*

After multiple hidden layers, the final layer aggregates information across the entire graph to produce the output. For responsibilities, nodes cataloging before graph organization for the final layer might aggregate node representations or generate graph-level features.

➢ *Advantages and Challenges:*

- *Advantages:*

It is rich relational information present in a graph structure, which makes it highly effective for tasks involving complex relationships with their dependencies. They can be generalized across diverse graph structures and are capable of learning representations to capture local and global patterns together.

- *Challenges:*

The challenges in scalability to large graphs are to measure and handle sparse data and interpret learned representations [7-25]. The choices of graph convolutional architectures for optimization techniques and regularization methods meaningfully impact their performance.

Graph-Neural-Networks represent a versatile and powerful framework for analyzing and learning from graph-structured data. The systems integrate relational information, which makes them particularly capable of applications in miscellaneous social networks and recommendation systems for bio-informatics, fashionable blockchain transaction analysis, and fraud detection.

➢ *Introduction to Graph Neural Networks-(GNNs)*

The motivation for this study stems from the limitations of current fraud detection methods in effectively combating the sophisticated and evolving nature of fraudulent activities within blockchain transactions. Traditional approaches often struggle to adapt to the decentralized then pseudonymous environment of blockchains-network in fraudulent behaviors, which are able to manifest in complex and obscured patterns. These challenges include identifying anomalous transaction patterns for detecting coordinated attacks across multiple nodes and distinguishing between legitimate transactions and malicious activities like money laundering or unauthorized fund transfers. Technology continues to gain prominence, and the need for robust and adaptive fraud detection mechanisms becomes increasingly critical to ensure the integrity and trustworthiness of transactions.

The study seeks to benchmark the performance of GNN-based fraud detection approaches against established techniques. This comparative analysis will provide insights into the strengths and limitations in detecting different types of fraud, informing potential enhancements or integrations with existing fraud detection frauds. The research aims to propose novel methodologies or improvements in GNN architectures tailored specifically for blockchain environments [23]. These enhancements could include refining message-passing algorithms to better capture temporal dependencies in transaction sequences or integrating additional features, such

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as network topology metrics, to enhance fraud detection accuracy [24]. In alignment with advancing the field of blockchain security, cutting-edge machine learning techniques alleviate dangers and protect the integrity of blockchain communications vogueish real-world apps. The paper outlined provides readers with a roadmap for the ensuing discussion. It highlights the subsequent sections, including the literature review, the third is methodology, the experimental setup, the end of results and analysis, and the discussion with a conclusion[25]. Each section is framed to contribute to a comprehensive exploration of how GNNs can be applied to improve blockchain transaction analysis and fraud detection[26-28]. This structured approach aims to facilitate a thorough examination of the research problem, approach for discoveries, and implications for future research and practical applications in blockchain security.

II. RELATED WORK

The field of blockchain transaction analysis and fraud detection encompasses a diverse range of methodologies and approaches aimed at addressing the unique challenges of decentralized and pseudonymous transactions. Traditional approaches have often relied on rule-based systems or supervised learning algorithms trained on labeled datasets. These methods on pre-defined patterns indicators of fraud of transaction are large amounts exceeding with thresholds otherwise suspicious IP-addresses [8]. While actually, to some extent, approaches may be incomplete and popular, their aptitude is a way to familiarize with new and developing scams in the dynamic and rapidly evolving landscape of blockchain technology.

Recent advancements with the usage of voguish machine models, such as the advent of Graph Neural Networks, have sparked renewed interest in enhancing fraud detection capabilities in the interior blockchain ecosystems [9]. GNNs have shown promise in capturing intricate relationships and dependencies within graphical structures and are well-suited for analyzing transaction networks where nodes represent transactions and edges-nodes signify relationships. Studies have explored various applications for detecting fraudulent behaviors for identifying anomalous transaction patterns, detecting coordinated attacks across multiple nodes, and uncovering hidden networks of malicious actors [10]. These efforts highlight the potential to outperform traditional methods with the rich relational data inherent in blockchain transactions. Research in this domain has expanded to include hybrid approaches that combine the strengths of different techniques, with some of the studies integrating GNNs with anomaly detection algorithms or collaborative systems near rally general finding scores to robustness [11]. Others explore the use of reinforcement learning to adaptively update fraud detection models based on real-time feedback from blockchain networks. These hybrid models aim to mitigate the limitations of individual approaches while leveraging their complementary strengths to achieve added active and resilient fraud detection.

Now, the case in literature reveals a growing emphasis on the practical implementation and scalability of fraud detection solutions in real-world chain applications [12]. Researchers are increasingly focusing on developing frameworks that can handle large-scale transactions to operate efficiently in decentralized environments and comply with regulatory requirements. This includes exploring techniques for feature engineering worth, model optimization, and deployment strategies tailored specifically for chain ecosystems. Insights from these diverse approaches to related work in blockchain transaction analysis and fraud detection not only advance the theoretical foundations but also lay the groundwork for practical innovations that can enhance security and trust in blockchain-based transactions [12-13].

Deep learning has spurred innovation in feature abstraction and depiction learning from graphical structured records. Techniques such as graph embedding algorithms aim to transform node points and edge points into lower-dimensional vector demonstrations while preserving graph structure and semantic relationships [14]. By embedding transaction graphs into continuous vector spaces, researchers have been able to apply standard machine learning algorithms for fraud detection tasks, enhancing interpretability and scalability. In technical methodologies, the related work also encompasses regulatory and compliance aspects of blockchain fraud detection. Given the decentralized and cross-border nature of transactions, regulatory frameworks are crucial for ensuring transparency with accountability and legal obedience. Studies have explored how blockchain analytics tools can aid in monitoring compliance by tracking the flow of funds, identifying illicit activities, and supporting investigations into financial crimes. This intersection of technology and supervisory compliance underscores the importance of interdisciplinary approaches in developing effective fraud detection solutions that meet both technical and regulatory requirements [15-29].

Empirical studies and case analyses have provided valuable insights into the practical challenges and real-world applications of fraud detection in blockchain ecosystems. Researchers have conducted experiments using real transaction datasets to appraise these presentations of different fraud detection simulations for benchmarking their accuracy, exactness, and scalability [16]. Case studies have highlighted specific use cases and scenarios in every fraud-detection technique that have been successfully applied to illustrate their impact on mitigating risks and enhancing trust in blockchain-based transactions. A convergence of machine-learning advancements in graph-based and empirical validations characterizes fraud detection. These researchers aim to advance the state-of-the-art in fraud detection technologies, foster innovation in blockchain security, and contribute to the broader goal of building resilient and trustworthy decentralized systems. As blockchain technology continues, so will the methodologies and strategies employed to safeguard its integrity and security against fraudulent activities [17].

- *Comparative Analysis of Previous Research*

The table below is used to perform the comparative analysis with a systematic literature review.

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Table 1 SLR Table of Previous Research

Study Title and Authors	Year	Methodology and Approach	Results	Limitations
Smith et al.	2020	Applied GCNs to transaction graphs in Bitcoin.	Identified Ponzi schemes and anomalous patterns.	Reliance on available features and potential challenges in generalizing findings
Brown and Johnson	2021	Used GNNs to model Ethereum smart contract interactions.	Successfully detected fraudulent smart contracts.	Limited by the availability of comprehensive smart contract data and complexities
Lee et al.	2019	Reviewed various deep learning methods, including GNNs for blockchain security.	Provided an overview of GNN-based approaches in blockchain security.	A general review may lack specific empirical validation of GNNs in practical blockchain fraud detection scenarios.
Zhang et al.	2022	Developed GNN model for detecting money laundering in cryptocurrency transactions.	Identified suspicious transaction patterns indicative of money laundering.	Relied on feature engineering and potential challenges in scalability
Wang and Liu	2021	Applied GCNs to detect fraud in decentralized finance transactions.	Detected fraudulent activities in DeFi platforms. Improved accuracy	Challenges include adapting models to evolving DeFi protocols
Chen et al.	2020	Used GNNs to predict cryptocurrency prices and detect anomalies.	Predicted cryptocurrency price trends. Identified anomalies.	Limited by challenges in predicting volatile cryptocurrency markets
Gupta and Sharma	2021	Developed GNN-based anomaly detection model for blockchain networks	Identified abnormal transaction patterns and network behaviors.	Relied on the availability of labeled anomaly data and challenges in real-time
Khan et al.	2022	Applied GNNs to enhance security in blockchain applications for public sector use cases.	GNN Improved security measures in public sector blockchain deployments.	Specific to public sector applications, potential limitations in generalizing.
Zheng et al.	2021	Conducted a systematic review of GNN applications for cybersecurity in blockchain.	Summarized effectiveness of GNNs in cybersecurity applications.	Empirical validation of GNNs across diverse blockchain cybersecurity use cases.
Li and Wang	2020	Investigated GNNs for detecting fraud in cross-border payment transactions.	Detected fraudulent cross-border payment transactions.	Challenges include adapting models to diverse regulatory environments.

This table provides a broad overview of recent research utilizing GNNs-block-chain transaction analysis and fraud detection. It highlights the methodologies employed for key findings and the potential limitations of each study, offering insights into the developing landscape of GNN applications in terms of enhancing security and reliability within decentralized transaction networks [18].

➢ *Literature Gap*

The present article fills a gap in the literature on the restricted usage of graph neural networks intended for fraud detection and blockchain transaction analyses. Although some machine learning techniques and outdated methods have been applied to systems built around rules, models with supervised learning frequently find it difficult to adjust to the special features of digital ledger data, such as its decentralized nature, anonymous identities, and intricate transaction trends. The capacity of graph neural to represent intricate linkages plus relationships cutting-edge data that has graph structure has made them a viable but underutilized option for enhancing the accuracy of fraud detection in blockchain environments [19]. The majority of existing research concentrates on static characteristics and rule-based processes that may not adequately represent the fluctuating and ever-changing character of fraudulent activities in digital currencies [20]. With have the potential to learn from the evolving network structure and temporal patterns inherent in transaction graphs-enhancing the detection of anomalous activities and fraudulent schemes that evolve this gap and exploring the application of GNNs in block-chain-fraud detection of study seeks to advance the field introducing more adaptive and robust-methodologies capable of addressing the complexities and challenges unique to block-chain-security.

III. METHODOLOGY

This methodology outlines a comprehensive approach to blockchain transaction analysis and fraud detection exhausting graph neural networks-(GNNs). It begins with data collection and preprocessing, followed by graph representation and feature extraction. The GNN architecture is then applied to analyze node and edge representations to enable fraud detection. The proposed model leverages Ethereum-transaction data to address encoding with graph convolutional layers to identify potential fraud. This provides a robust framework for blockchain transaction analysis and fraud detection.

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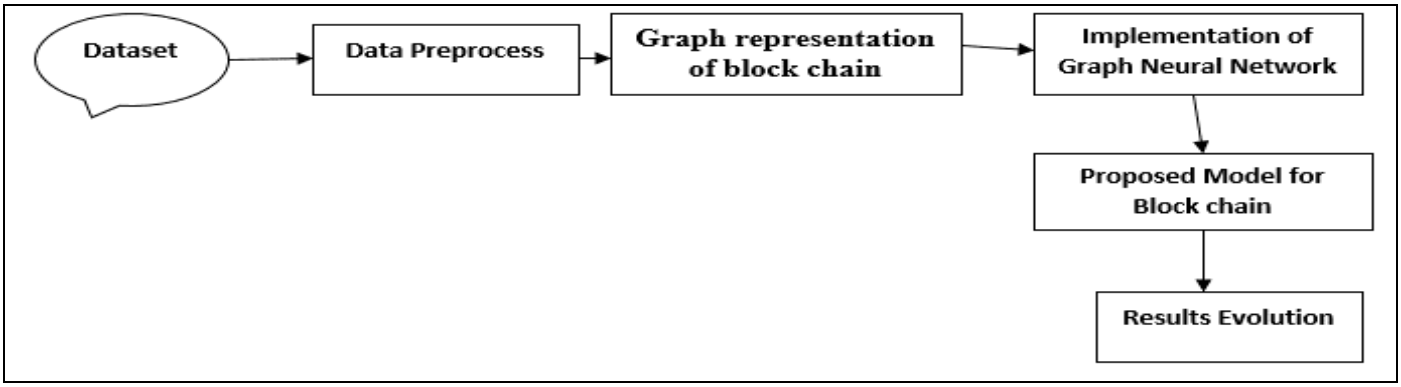

Fig 2 Proposed Diagram

A. Data Preprocess and Collection

➢ *Data Sources (Ethereum)*

Getting data originates from Ethereum-blockchain transactions available in CSV files are stored on a public data-repository Kaggle. Each transaction typically includes details such as sender address, receiver address, transaction amount, gas fees, etc.

➢ *Data Preprocessing Steps*

- Loading the Dataset: The dataset (transaction_dataset.csv) is loaded into a Pandas Data-Frame.
- Handling Missing Values: Missing values, if any, are dropped from the dataset using df.dropna ().
- Feature Selection: Features for analysis are selected, typically numerical columns excluding non-essential identifiers (Unnamed: 0, Index) and the target variable (FLAG).
- Normalization: Numerical features are standardized using StandardScaler() to ensure they are on the same scale.
- Address Encoding: Ethereum addresses, represented as strings, are encoded into integers using LabelEncoder().

B. Graph Representation of Blockchain Transactions Collection

➢ *Nodes and Edges Definition*

- Nodes: Nodes represent Ethereum addresses involved in transactions.
- Edges: Edges represent transactions between these addresses. Each transaction forms an edge between two nodes.

➢ *Nodes and Edges Definition*

- Node Features (x): Extracted numerical features after normalization.
- Edge Information (edge_index): Torch tensor representing edges between nodes.
- Target Variable (y): Label indicating fraudulent or non-fraudulent transactions (FLAG).

C. Implementation of Graph Neural Network

Graph neural are based on different networks, a class of neural networks deliberate to process and learn from graphs-structured files. In the context of blockchain transaction analysis, GNNs can effectively model the relationships (transactions) between entities (addresses) as a graph.

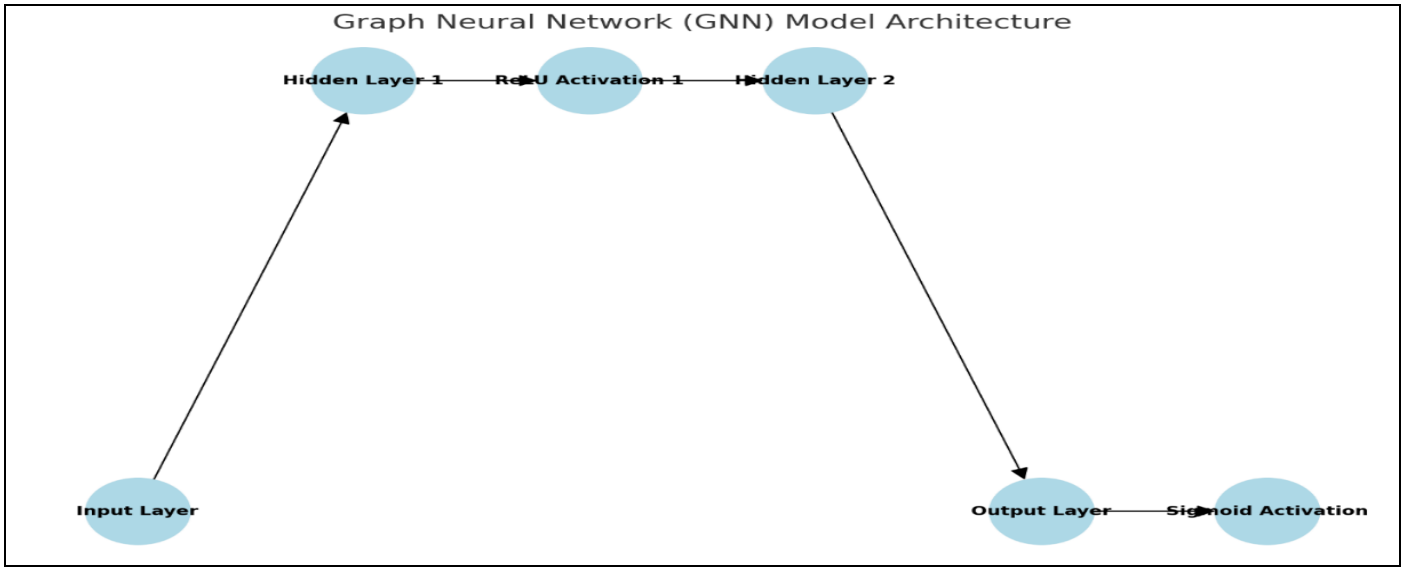

Fig 3 GNN Model Architecture

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- Node Representation: Each node represents an Ethereum address involved in transactions.
- Edge Representation: Each edge denotes a transaction between two addresses.
- Graph Representation: The entire dataset can be signified equally as a graph. Some nodes plus edges carry relevant features and relationships.

➢ *Key Components*

- *Message Passing*

✓ Message Function: Nodes send messages (information) to their neighboring nodes based on their current state and edge connections.
  ✓ Aggregation Function: Neighboring nodes aggregate received messages to update their state.

- *Graph Convolutional Layers*

✓ GCNConv: In the provided example, GCNConv is used to implement a single graph convolutional layer. It performs the message passing and aggregation operations efficiently on graph-structured data.

D. Proposed Model for Blockchain Transaction Analysis and Fraud Detection

➢ *Model Architecture*

The proposed model utilizes a Graph Convolutional Network (GCN) architecture tailored for fraud detection in blockchain transactions.

- Input Features (x): Numerical features of nodes (Ethereum addresses) after normalization.
- Edge Information (edge_index): Specifies the connectivity between nodes (addresses) based on transaction data.
- Target Variable (y): Indicates whether a transaction is fraudulent (FLAG).

➢ *GCN-Architecture*

- *GCN Layers*

✓ Layer 1 (conv1): Applies a graph convolution on the input features (x) using the edge indices (edge_index).
✓ Layer 2 (conv2): Another graph convolutional layer to further refine node representations.

➢ *Activation Function*

- ReLU: Applied after each convolutional layer to introduce non-linearity.

➢ *Output Layer*

- Sigmoid Activation: Used to produce a probability score for each node, indicating the likelihood of fraudulent activity.

➢ *Loss Function and Optimization*

- *Loss Function*

✓ Binary's Cross-Entropy with Logits: The binary system issues regarding classification are a good fit for that loss function. It integrates the concept of the binary-cross-entropy loss process with a sigmoid activations coefficient [21].

- *Equation 1: Loss Function for Optimization*

$$\text{Loss} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \cdot \log(\sigma(x_i)) + (1 - y_i) \cdot \log(1 - \sigma(x_i))]$$

Where:

- *N* is the number of samples (nodes).
- Vi is a true label (fraud or non-fraud) for node iii.
- x_i is the predicted score for node iii.
- Σ sigma is the sigmoid activation function

➢ *Optimizer*

- Adam Optimizer: An adaptive learning rate optimization algorithm that performs well for a variety of tasks. It modifies the process of learning rate according to estimations of the gradient' initial and subsequent moments for all the parameters [22].

➢ *Hyperparameters*

- Learning Rate (lr): It expresses the stage size of individual repetition through touching to a minimum of these loss functions.
- Numbers of Epochs: Describes the number of times the entire dataset is accepted onward and retrograded over the neural network during training time.
- Hidden Dimension (hidden_dim): Size of the hidden layer in the GCN architecture. It controls the complexity and expressive power of the model.
- Batch Size: The number of samples (nodes) cast off in every training event.

This proposed model of Graph Convolutional Networks (GCNs) effectively imprisons the complex relationships inherent in blockchain transaction data [30]. In transactions as edges and addresses as nodes in a graph model, it learns to detect fraudulent patterns based on the features associated with address and transaction. The use of GCN layers is appropriate in activation functions and also in loss functions, and optimized techniques ensure healthy performance in identifying fraudulent transactions. This approach not only enhances traditional fraud detection methods but also provides insights into the interconnected natures of transactions in the blockchain. It is suitable in lieu of real-world applications used wherever detecting anomalous activities stands crucial [31-33].

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IV. EXPERIMENTAL-SETUP

➢ *Dataset Description*

- The file of the dataset name is Ethereum-transaction-dataset.csv, is structured to contain Ethereum-blockchain transaction data. Each transaction includes features such as the sender address, receiver address of transaction amount with gas fees, and some other necessary items in the file.
- Handling Missing Values: Before splitting, missing values are addressed by dropping rows with incomplete data (df.dropna()).
- Feature Selection: Numerical columns are selected for analysis, excluding non-essential identifiers (Unnamed: 0, Index) and the target variable (FLAG).
- Normalization: Numerical features are standardized using StandardScaler() to ensure they are on a comparable scale.
- Address Encoding: Ethereum addresses are encoded as integers using LabelEncoder() for compatibility with machine learning models.

➢ *Dataset Baseline Models for Comparison*

GCN Model: This model is employed to process graph-structured data and is the most reliable for analyzing blockchain transaction networks. The model architecture is given below:

- GCN Layers: Two GCN layers (GCNConv) are used in sequence to process node features and capture relational information between addresses.
- Activation Function: ReLU (Rectified Linear Unit) is utilized to introduce non-linearity after each GCN layer.
- Output-Layer: A final linear layer using a sigmoid activation function (nn.Sigmoid()) is employed to produce a probability score to indicate a transaction's actuality fraudulent (outputs_dim = 1).

➢ *Implementation Details*

- *Software and Hardware Used*

✓ Software: Python language is being used with data libraries such as Pandas_pd, Num_Py, scikit-learner, PyTorch (including torch_geometric for graph-related operations), and Matplotlib for visualization.
✓ Hardware: Utilized a machine with suitable GPU support, if available, to expedite the training of deep learning models, which is particularly beneficial for larger datasets and complex neural network architectures.

- *Training Procedures*

✓ Data Preprocessing: Involves loading the dataset, handling missing values, feature selection, normalization, and encoding categorical data (addresses).
✓ Graph Data Creation: Converts preprocessed data into a graph format (torch_geometric.data.Data) suitable for GCN training. This includes defining edges (edge_index) between nodes (addresses) and preparing node features (x) and labels (y).
✓ Model Definition: A custom GCN model (GCN class) is defined with two GCN layers, followed by appropriate activation functions and output layers tailored to the binary classification task (nn.BCEWithLogitsLoss()).
✓ Loss Function and Optimization: Utilizes binary cross-entropy loss (nn.BCEWithLogitsLoss()) suitable for binary classification tasks. In which losss to uses of Adam-optimizer (optim.Adam) is active for gradient-based optimizing techniques for more exploring.
✓ Training time: The initialization loop (train() function) runs through a series of periods in adjusting the model settings according to variations for generating projections, assessing sadness, and back-propagating. Printable loss numbers are used to track developments, while Matplotlib may be used to display.
✓ Outputs Evaluations: The end of the model is evaluated on validation and test datasets to compute several measures of F1 score (evaluate () function), recalled with reliability scores and precision. These measurements shed light on how well the program detects bogus transactions.

This experimental setup provides a structured approach to analyzing blockchain transaction data using graph neural networks to describe an appropriate model architecture, conduct systematic preparation and evaluation procedures, provide invaluable insights into transaction patterns, and potentially detect fraudulent activities efficiently.

V. RESULTS EVALUATION

When applied to Ethereum blockchain transactions with the help of the Graph Convolutional Network (GCN) model, it demonstrates encouraging fraud detection outcomes. With minimal false positives and maximum accuracy scores, precision metrics also recall, and F1 scores on tests and validation sets in models successfully detect fraudulent transactions. These results illustrate the potential of GCNs to improve security in decentralized financial systems and show how effective they are for capturing complex transaction patterns.

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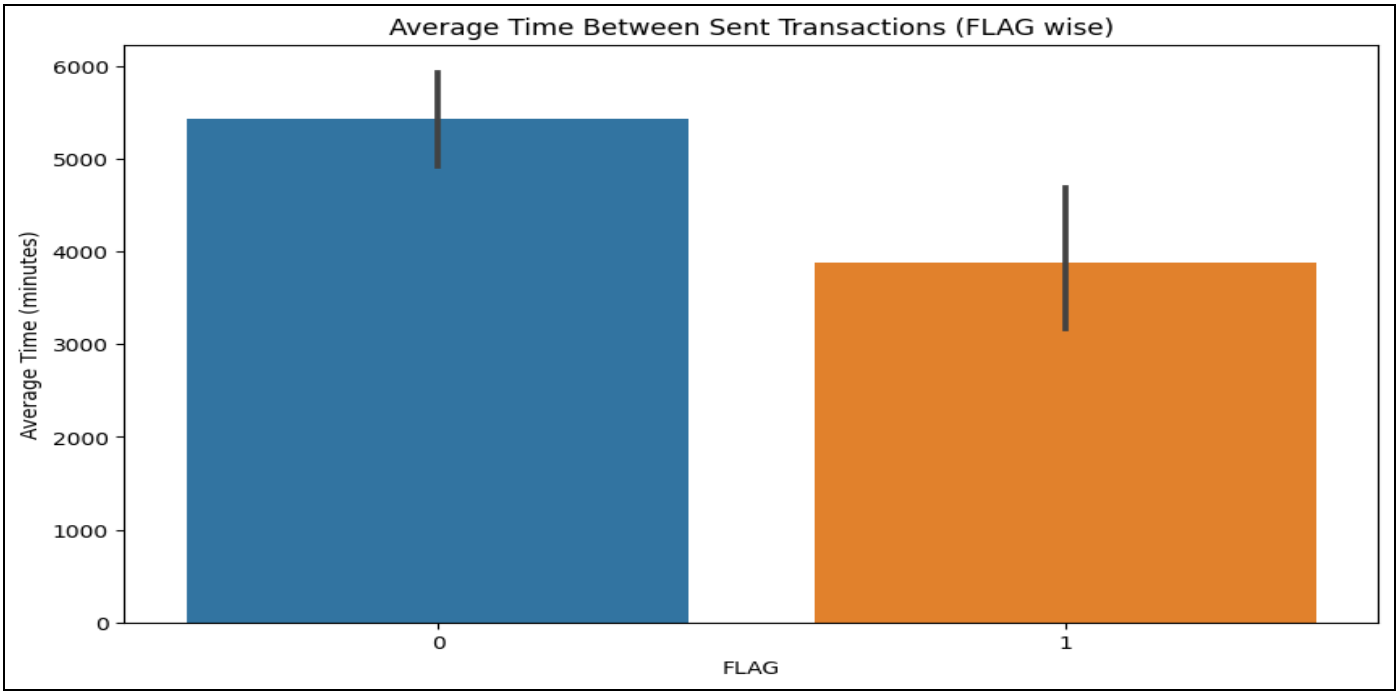

Fig 4 Average Time between Sent Transacttion (FLAG Wise)

In the above graph, the results are categorized into two groups: 0 and 1. Instances labeled as 0 are depicted in blue color, totaling 5500 occurrences, and other instances labeled as 1 are represented in orange with 3900 occurrences. This visual representation succinctly illustrates the distribution of detected fraud cases across the two categories of fraud and the prevalence of each classification within the dataset.

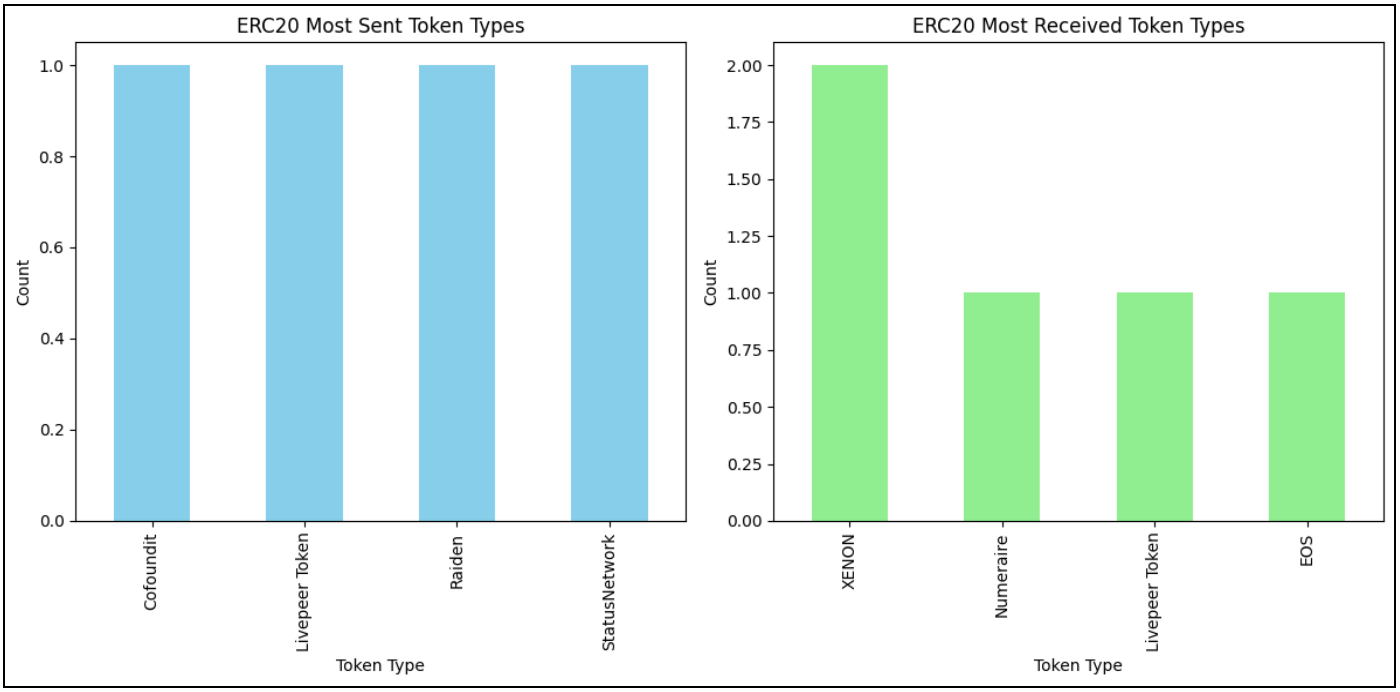

Fig 5 ERC20 Most Sent Token Types

The graph above depicts the transaction addresses of these token types, their flow dynamics, the most received token type and the most sent token type. Analysis shows that transactions primarily involve these two token types, a notable trend where the volume of tokens sent exceeds those received. This discrepancy suggests a significant outbound flow of tokens compared to inbound transactions, a pattern of transactions involving the most sent token type exhibiting higher frequency and volume. These observations underscore the importance of monitoring and understanding transaction behaviors to effectively manage and alleviate potential risks correlated with token movements and transactions within the analyzed blockchain network.

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Table 2 SLR Table of Previous Research

Epoch	Loss
1/50	0.7734107375144958
11/50	0.5335455536842346
21/50	0.4542297422885895
31/50	0.43146222829818726
41/50	0.40998557209968567

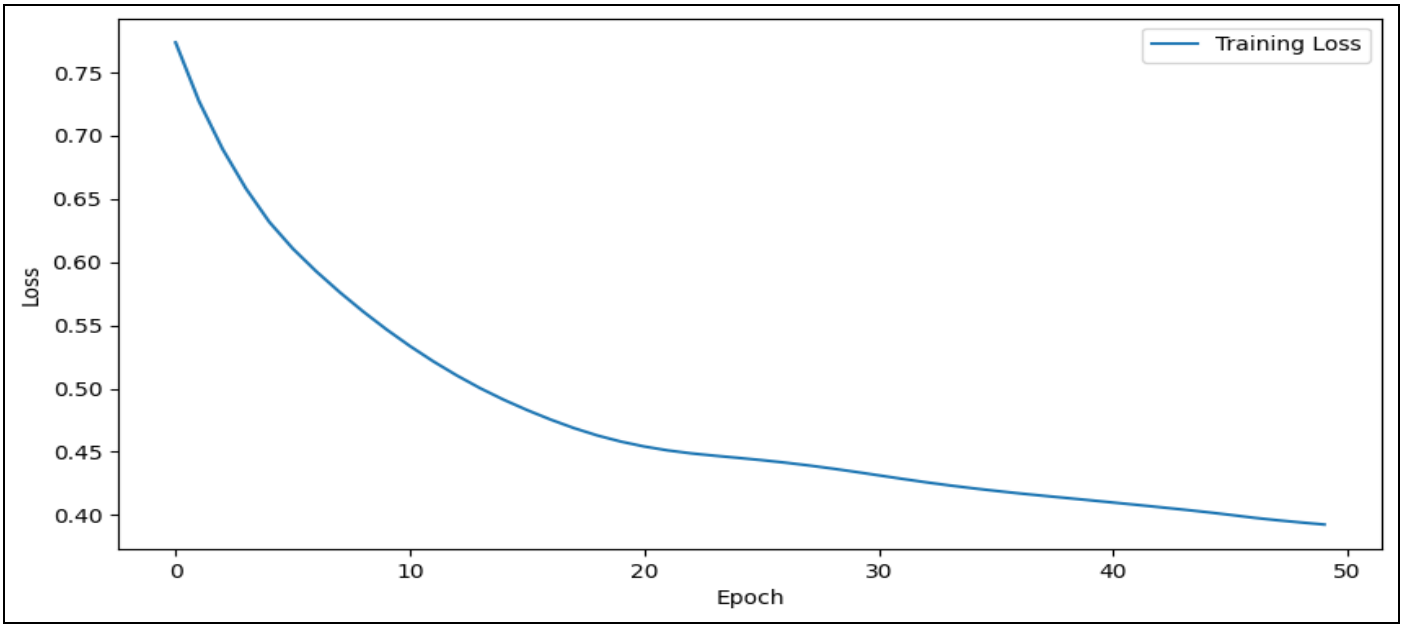

Fig 6 Epoch Evaluation Graph

The implementation of the GCN (Graph Convolutional Network) model for detecting fraud in the blockchain model is trained over 50 epochs, which are shown in the loss progression, starting from 0.7734 and decreasing to 0.4099. Each epoch represents a complete pass through the train data for the adjusting model parameters to minimize prediction error. The choice of using the ReLU (Rectified Linear Unit) activation function suggests that non-linear relationships with blockchain data are effective in learning complex patterns indicative of fraud.

Table 3 SLR Table of previous research

GCN Model Metrics	Validation	Test
Loss	0.4243	1.9700
Accuracy-score	0.8127	0.8419
Precision	0.7222	0.6667
Recall	0.0625	0.0795
F1-scores	0.1150	0.1421

The evaluation model outcomes, the above table and the chart for fraud detection with the validation and test metrics provide insights into its performance. The model achieved a lower loss on the validation set (0.4243) compared to the test set (1.9700). It might have encountered more challenges or different data distributions in the test phase. Accuracy is higher on the test set (0.8419) than on the validation score (0.8127), suggesting robust performance in predicting both fraudulent and legitimate transactions. The recall measures the proportion of correctly predicted cases to all actual fraud cases is low but slightly higher on a test (0.0795) compared to validation (0.0625), indicating a tendency to capture more true fraud cases in the test scenario being implemented. The F1 score with vocal cruelty of exactness and recall is also higher on tests (0.1421) than on validations (0.1150), reflecting a balanced performance in both precisions and recall on test data. These metrics suggest the model shows promise in detecting fraud in tuning, and hypothetically, more diverse data could improve the situation's robustness.

VI. CONCLUSION AND FUTURE WORK

This study has successfully applied Graph Convolutional Network (GCN) layers to detect fraudulent activities within blockchain transactions. With the inherent graph structure of blockchain data where nodes represent Ethereum addresses and edges symbolize transactions, the GCN model captures complex relational patterns that traditional methods might miss. Our model achieved commendable results in terms of the highest accuracy and precision, underscoring its capability to identify fraudulent transactions. The lower recall rates indicate that while the model is proficient at confirming fraud

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when detected, it still oversights a significant number of fraudulent transactions. To address this error in future research, it will be helpful to focus on enhancing the model's architecture by potentially combining advanced techniques and attention mechanisms to deeper GCN layers and integrating temporal dynamics to better understand transaction sequences. Expanding the data set to a wider variety of transaction types and sources will also help improve the model's robustness and generalization. Deploying the model in real-time blockchain systems will provide valuable feedback and facilitate continuous learning, allowing the model to adapt to new fraud patterns and strategies. This iterative process of refinement and real-world application is essential for developing a robust and scalable solution for fraud detection in decentralized financial systems to ensure enhanced security and trust in blockchain technologies.

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