Fraud Detection in DeFi Using Transaction Graph Embeddings and GNNs

A Project progress Report

BACHELOR OF TECHNOLOGY
[Information Technology]

To

Dr. A.P.J. ABDUL KALAM TECHNICAL UNIVERSITY, LUCKNOW

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ABSTRACT

Decentralized Finance (DeFi) has emerged as a rapidly growing ecosystem enabling peer-to-peer financial transactions without centralized intermediaries such as banks or exchanges. Despite its innovation, DeFi remains vulnerable to malicious activities including phishing, rug-pulls, money laundering, Ponzi-style schemes, and exploit-based attacks. Detecting such fraudulent behaviour is challenging due to anonymity, dynamic wallet interactions, and the absence of regulatory identity validation. This project aims to develop an intelligent fraud detection framework that leverages transaction graph embeddings and Graph Neural Networks (GNNs) to identify suspicious patterns in DeFi networks.

In the proposed system, blockchain transaction data is represented as a directed heterogeneous graph where nodes denote wallet addresses and edges represent transactions containing attributes such as value, frequency, and timestamp. Features including transaction counts, time-based spending behaviour, contract interactions, token flow patterns, and historical balances are extracted to capture real-world behavioural semantics. Graph embedding techniques such as Node2Vec, Deep Walk, and Graph SAGE are used to encode addresses into low-dimensional feature vectors, preserving structural and relational characteristics.

A GNN-based model is then trained on labelled datasets containing known fraudulent and legitimate wallet addresses. Variants such as Graph Convolutional Networks (GCN), Graph Attention Networks (GAT), and Temporal GNNs are evaluated to capture evolving transaction dynamics. The system performs classification for fraud detection, and anomaly scoring for unknown suspicious nodes. Additionally, attention weight visualization helps identify influential transaction paths, enabling interpretability for analysts.

Experimental evaluation will be performed on publicly accessible Ethereum DeFi transaction datasets. Performance will be measured using Precision, Recall, F1-Score, ROC-AUC, and False-Positive Rate to ensure robust fraud detection. The expected outcome is a scalable fraud prediction model that learns evolving transaction patterns, detects malicious entities prior to large-scale losses, and supports forensic tracing of illicit flows.

ACKNOWLEDGMENT

We are deeply grateful for the support and guidance that helped us successfully complete this project titled "**Fraud Detection in DeFi Using Transaction Graph Embeddings and GNNs.**"

First and foremost, we would like to express our sincere gratitude to our project mentor for providing valuable insights, continuous encouragement, and constructive feedback throughout the progress of this work. Their guidance played a crucial role in shaping our understanding of decentralized finance, fraud detection techniques, and modern graph-based machine learning approaches.

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Moreover, we extend our appreciation to our team members for their collaboration, discussions, and collective effort in completing this project. Their dedication and teamwork were essential to the execution and development of the system.

Finally, we are thankful to our families and friends for their encouragement and support throughout this journey. Without their constant motivation, this work would not have been possible.

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INTRODUCTION

The emergence of blockchain technology has enabled a completely new financial ecosystem called Decentralized Finance (DeFi). DeFi allows users to perform financial operations such as lending, borrowing, token exchange, staking, crowdfunding, and automated payments without relying on traditional financial intermediaries like banks, brokers, or regulatory authorities. Built on smart contracts, DeFi applications operate transparently over public blockchain networks where all transactions are traceable and permanently recorded. This innovation promotes inclusiveness, accessibility, security, and programmability in financial services.

However, with the growth of DeFi platforms, fraudulent activities have also rapidly increased. Due to anonymity, lack of identity verification, and rapidly evolving smart contract interactions, malicious users exploit vulnerabilities to steal funds, deceive users, manipulate token values and perform criminal transactions. Conventional techniques used in banking such as centralized monitoring, KYC validation, user account tracking, or identity tracing do not exist in decentralized systems. Therefore, there is a need for intelligent automated systems that can analyze blockchain transactions and detect fraud patterns.

To address these challenges, the present project focuses on fraud detection using **Transaction Graph Embeddings** and **Graph Neural Networks (GNNs)**. By transforming blockchain data into graph embeddings, the structural patterns of interaction are encoded into vector representations. GNNs then learn relationships between wallets and classify malicious nodes. This project enables automated detection of suspicious wallet activities and reduces risks associated with decentralized financial operations.

1.1 Background

Decentralized Finance (DeFi) is a blockchain-based financial ecosystem that enables activities such as asset transfer, trading, lending, investment, and staking without intermediaries. Unlike banking systems, DeFi provides open access, no-permission usage, and complete transparency of recorded transactions. However, due to anonymity of wallet addresses and no centralized monitoring body, fraudulent practices have increased significantly.

Some common frauds in DeFi are:

- Rug-pull scams
- Fake token circulation
- Transaction laundering
- Phishing-linked wallet attacks
- Multi-wallet coordinated theft

Since blockchain data is public but identity is hidden, identifying suspicious wallets is complex. Moreover, fraudulent activities involve interconnected wallets, repeated transfers, and abnormal patterns that cannot be identified using simple rule-based methods.

Machine learning enables pattern recognition but traditional models cannot analyze relationships among thousands of wallet interactions. Therefore, advanced techniques like **Graph Neural Networks (GNNs)** and **Graph Embeddings** are used to detect fraud through transactional structures.

Blockchain transaction data naturally forms a graph where:

- **Nodes represent wallet addresses**
- **Edges represent transactions**
- **Edge properties include value, timestamp & direction**

Graph learning helps identify groups of risky wallets, hidden patterns, and abnormal fund flows efficiently.

Hence, this project focuses on analyzing blockchain graphs and detecting fraud using **Graph Embedding and GNN-based classification**.

1.2 Federated Learning in DeFi Fraud Detection

Federated Learning (FL) is a decentralized model training technique where multiple blockchain data holders (exchanges, node validators, DeFi platforms, wallet monitoring systems) collaboratively train a shared fraud detection model without sharing raw transactional data. Instead of exchanging actual wallet histories or sensitive transaction logs, each participant sends:

- Local model parameters
- Gradient weights
- Partially learned fraud embedding vectors

This is useful because financial transaction data on DeFi platforms is highly sensitive, and certain platforms maintain proprietary risk databases.

Federated Learning Architecture for Defi fraud Detection

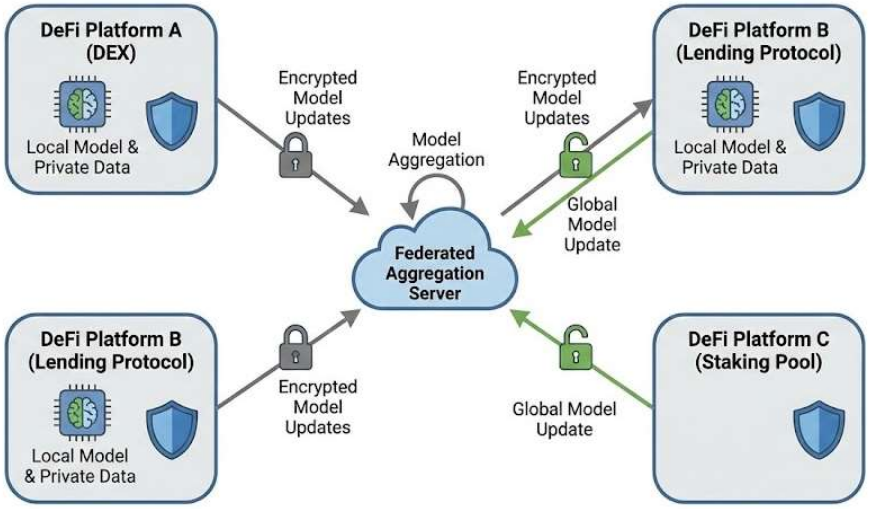

Figure 1. Decentralized fraud detection model training without sharing raw data.

Why FL is Useful in DeFi Fraud Detection

DeFi platforms often maintain private:

- Suspicious wallet lists
- Risk scores
- AML (Anti-money laundering) traces
- Transaction anomaly patterns

Federated Learning allows platforms to combine their knowledge without exposing raw datasets.

Advantages of Federated Learning in DeFi

No Raw Transaction Sharing

Wallet data remains secure with the platform and never transferred externally.

Secure Multi-Exchange Collaboration

Different entities such as:

- CEX exchanges (Binance, Coinbase etc.)
- DeFi protocols (Uniswap, Aave)
- Blockchain analytics platforms (Chainalysis, Nansen)

Enables Cross-Chain Detection

Federated learning can aggregate signals across:

- Ethereum
- Polygon
- Binance Chain
- Solana

making fraud detection more universal.

Supports Scalability

- Federated learning distributes training across participating nodes,
- reducing load on a central server.
- Challenges of Federated Learning in DeFi Fraud Detection

1. Privacy Leakage :

- Although raw transactions are not exchanged,
- attackers may still extract wallet traces through:
- Gradient inversion
- Model reconstruction attacks
- Transaction trend inference

For example:

A malicious aggregator can approximate a user's spending pattern.

2. Non-IID Data Problem in DeFi:

- Transactions differ based on:
- Platform type (DEX, lending, gaming, NFT)
- Token usage patterns
- Investor demographics
- Market phase (bull vs bear cycle)

This makes FL unstable because:

- Some nodes have extremely dense graphs

- Some have sparse transaction history

which decreases accuracy.

3. Malicious Nodes:

In DeFi:

Some clients may intentionally poison the model.

Examples:

- Providing false fraud labels
- Sending manipulated embeddings
- Increasing weights of fraudulent wallets
- Lowering weights of scam-associated clusters
- This leads to unsafe global model performance.

4. Lack of Auditing, Logging & Traceability:

- Classical FL cannot clarify:
- Which node contributed which update
- Whether an update was trustworthy
- Which wallet embeddings caused misclassification
- Whether aggregation was manipulated

As a result:

A compromised platform can influence fraud detection globally.

1.3 Problem Statement

Fraudulent wallet detection in DeFi is difficult because:

- Wallet holders remain anonymous
- Transaction amounts vary highly
- Attackers use multiple forwarding wallets
- Smart contract-based fraud evolves continuously
- Traditional monitoring systems cannot track graph-based behavior

Therefore:

There is a need to detect suspicious wallet behavior by analyzing transaction relationships using Graph Neural Networks and graph embedding techniques rather than simple transaction-wise classification**.**

1.4 Objectives

The major objectives of this project include:

Primary Objectives

- To convert blockchain transactions into graph-based structures
- To generate node embeddings using techniques like Node2Vec or GraphSAGE
- To train Graph Neural Network models for classification of suspicious wallets
- To detect abnormal fund flow and behavioral anomalies

Secondary Objectives

To perform evaluation using accuracy, precision, recall, and F1-score
To highlight suspicious wallet clusters visually
To provide automated fraud detection prediction

1.5 Motivation

- More than **$2.2 billion was lost in DeFi scams and hacks in the last two years**
- 68% of wallet-based thefts involved **chain-based transfers**
- Majority of fraud uses **temporary wallets created only for one-time access**

From these facts, fraud detection becomes necessary for:

- Investors
- Crypto exchanges
- DeFi applications
- Blockchain analysis platforms

1.6 Scope of the Project

This project focuses on:

- Ethereum-based transaction dataset
- Wallet-to-wallet transfer behavior
- Detection of abnormal transactions
- Embedding-based classification

1.7 Proposed Method Summary

The system follows key steps:

Step 1: Dataset Collection

- Extract transaction history
- Map senders, receivers, timestamps, and transfer value

Step 2: Graph Construction

- Nodes = Wallets
- Edges = Transactions

Step 3: Feature Engineering

Examples:

- Number of incoming transfers
- Wallet age and activity
- Transaction amount range
- Contract-based interactions

Step 4: Graph Embedding Generation Using:

- Node2Vec
- GraphSAGE
- DeepWalk

Step 5: GNN Classification Model

Possible models:

- GCN – Graph Convolutional Network
- GAT – Graph Attention Network

Step 6: Result Evaluation Metrics

- Accuracy
- F1-Score
- Precision & Recall

1.8 Expected Outcomes

The expected outcomes include:

- Automatic detection of suspicious and high-risk wallets
- Graph-based mapping of fund-flow patterns
- Reinforcement of security in DeFi platforms

Additionally, insights can be given to:

- DeFi developers
- Exchange-based compliance units

1.9 Chapter Summary

This chapter introduces the concept of DeFi and challenges associated with fraudulent transactions. It highlights why traditional methods fail and why graph-based deep learning is suitable for analyzing blockchain behavior. The chapter also defines objectives, problem statement, project scope, methodology flow, and expected outcomes.

Chapter 2

Literature Review

This chapter presents an overview of existing research related to fraud detection in decentralized finance (DeFi), blockchain transaction analysis, graph-based learning, and graph neural networks (GNNs). Recent studies highlight that transactional networks contain structural patterns, and graph representation improves fraud detection accuracy compared to traditional learning techniques.

2.1 Overview of Existing Work

Most existing fraud detection systems in financial domains rely on statistical rules, supervised machine learning models, or transaction-based classifiers. However, DeFi operates on blockchain networks where transactions create interconnected structures rather than isolated records. Thus, researchers have shifted towards treating blockchain data as a **graph**, where:

- Wallets → Nodes
- Transfers → Edges
- Transaction value, time, and frequency → Node/edge attributes

2.2 Research Trend in Fraud Detection

Recent research shows that converting such transactional graphs into embedding spaces allows machine learning models to learn relational behavior effectively. Graph Neural Networks are widely preferred as they analyze multiple relationships across connected wallets and detect suspicious patterns at neighborhood level.

Researchers have introduced multiple solutions focusing on:

- **Graph Representation of Transactional Data**
  Studies model blockchain data as directed or heterogeneous graphs to reveal communities, abnormal flows, and hidden wallet groups.

- **Graph Embedding Methods**
  Approaches like Node2Vec, DeepWalk, GraphSAGE, and domain-specific extensions capture structural similarities between nodes, helping detect clusters of fraudulent wallets.
- **GNN-Based Classification Models**
  Recent papers demonstrate that GNN models outperform conventional models because they incorporate:

Multi-hop neighborhood analysis

- Edge weight features such as amount, frequency
- Temporal changes and repeated patterns

Hybrid Detection Approaches
Some studies combine behavioral analytics (transaction timing, contract calls, gas usage) with graph-based embeddings to improve prediction accuracy.

2.3 Summary of Related Studies

Several prior studies focus on financial security using graph-based learning. Key findings include:

- Studies on money laundering detection proposed graph-aware embeddings that highlight illicit flow chains.
- Research on phishing and scam detection extracted small subgraphs around suspicious addresses to detect malicious activity patterns.
- From these studies, the major conclusion is that **graph context is critical**, as fraud is often not visible in a single transaction but becomes evident through repeated interactions over time.

2.4 Limitations of Existing Work

Although previous research has advanced significantly, some limitations still exist:

- Many studies focus on static transaction graphs even though blockchain data changes continuously.
- Limited datasets make training difficult because real fraudulent labels are difficult to verify.
- Interpretability of GNN models is still limited, making it difficult for analysts to trace decision reasoning.

These gaps justify the need for improved detection systems and more explainable graph-based models.

2.5 Relevance to Present Work

Based on existing literature, the present project uses:

- **Transaction Graph Representation** to capture wallet relationships
- **Graph Embedding Techniques** to convert graph structure into meaningful feature vectors
- **GNN-Based Learning Models** for classification and anomaly scoring

This helps detect abnormal transaction flow patterns, irregular connectivity structures, and suspicious wallet activities more accurately.

Chapter 3

Methodology and Proposed Tools

This chapter describes the methodology adopted for developing the fraud detection framework in decentralized finance (DeFi), along with the tools and technologies used for implementation. The overall approach follows standard data processing and machine learning stages adapted for blockchain transaction networks.

3.1 Methodology Overview

The methodology used in this project is divided into multiple systematic phases. Each phase contributes towards detecting suspicious wallet activities using graph-based machine learning techniques. The major steps include:

- **Dataset Collection**
- **Data Preprocessing**
- **Graph Construction**
- **Feature Engineering**
- **Graph Embedding Generation**
- **Model Training using GNNs**
- **Evaluation & Performance Measurement**

A workflow-based representation is shown below:

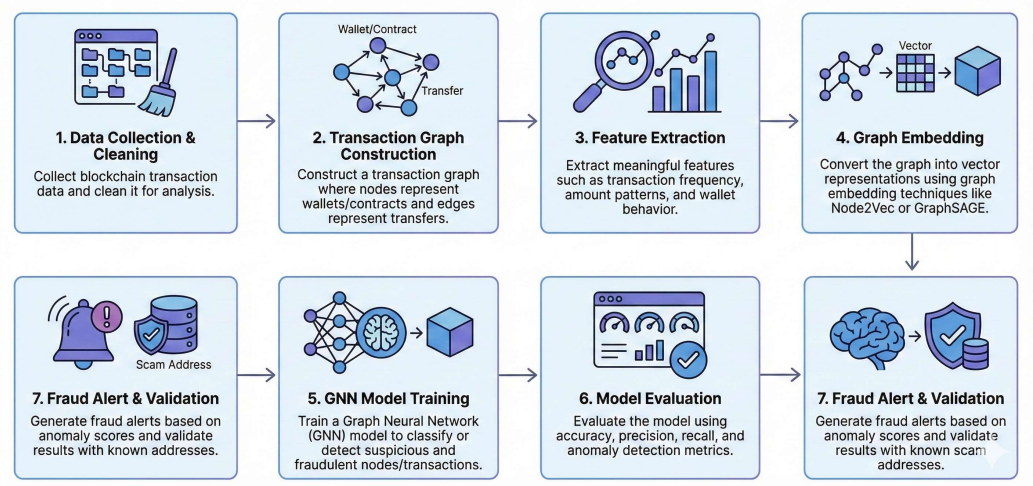

Figure 2

3.2 Phase-Wise Methodology Description

3.2.1 Data Collection

In this phase:

Blockchain datasets from DeFi protocols (Ethereum-based transactions) are gathered.Each record contains wallet addresses, transaction hash, amount, time, sender and receiver details.Data sources usually include public ledger dumps or blockchain explorers.

3.2.2 Data Preprocessing

The collected data is cleaned for:

- Duplicate transactions
- Missing timestamps
- Invalid addresses
- Extremely small noisy transactions
- Data normalization is also applied to ensure consistency in:

3.2.3 Graph Construction

In this step, raw records are transformed into graph structure:

- **Nodes** represent wallet addresses
- **Edges** represent transactions
- Edges are directed (sender → receiver)
- Edge attributes include:
- Transaction value
- Timestamp

This structure reveals clustering behavior, risky address chains, and repeated flows.

3.2.4 Feature Engineering

Both structural and behavioral features are extracted:

- **Wallet-based behavior**
- Number of incoming & outgoing transfers
- Contract interaction count

- **Graph-based properties**
- Node degree
- Edge frequency weight
- These features help improve classification accuracy.

3.2.5 Graph Embedding Generation

Graph embeddings convert node relationships into vector representation.

Methods used:

- **Node2Vec**
- **DeepWalk**
- **GraphSAGE**
- These embeddings preserve:
- Community structure
- Similar wallets appear closer in embedding space, aiding detection.

3.2.6 GNN-Based Model Training

Different Graph Neural Network (GNN) architectures are used, such as:

Graph Convolutional Network (GCN)
Learns neighbor influence using convolution-like propagation.

Graph Attention Network (GAT)
Assigns attention weights to important neighbors.

GraphSAGE GNN
Samples neighbors for scalable learning.

The model classifies each wallet as:

- Genuine wallet
- Fraud-suspected wallet

3.2.7 Model Evaluation

Performance metrics used:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC-AUC Score.

3.3 Proposed Tools & Technologies

Table 1

Category	Proposed Tools
Programming Language	Python
Dataset Handling	Pandas, NumPy
Graph Construction	NetworkX
Embedding Generation	DeepWalk, Node2Vec libraries
Machine Learning	PyTorch, TensorFlow
GNN Models	PyTorch-Geometric, DGL (Deep Graph Library)
Visualization	Matplotlib, Seaborn, Gephi (for large graphs)
Environment	Google Colab / Jupyter Notebook

3.4 Justification for Using Tools

- **Python**: High ML support & open-source libraries
- **NetworkX**: Direct graph creation & manipulation
- **PyTorch-Geometric / DGL**: Optimized frameworks for GNN models
- **Node2Vec**: Widely used graph embedding model
- **Gephi**: Best for visualization of large blockchain networks
- **Colab**: GPU support for faster training

3.5 Expected Output of Methodology

The proposed methodology aims to produce:

- Detection of suspicious wallet clusters
- Classification of fraudulent wallets
- Identification of risky transaction paths
- Improved fraud prediction accuracy using GNNs
- Better visibility of transaction relationships

Chapter 4

Security Analysis and Auditing Mechanism

This chapter focuses on analyzing security concerns in decentralized finance (DeFi) and the mechanisms used to audit and verify suspicious transactions using graph-based fraud detection systems. Since DeFi operates without centralized authorities, implementing automated auditing is essential to prevent financial losses, detect malicious patterns, and ensure safe participation in Web3 financial ecosystems.

4.1 Need for Security Analysis in DeFi

Traditional finance uses:

- Central authorities
- KYC-verified identities
- Fraud detection teams
- Transaction monitoring units
- Funds move instantly
- Assets are globally accessible
- Therefore, real-time monitoring and automated auditing of transactions are critical.

4.2 Security Risks in DeFi Platforms

Common security threats observed in DeFi include:

1. Phishing and Scam Wallets

Fraudulent wallets trick users into sending funds.

2. Money Laundering Chains

Multiple wallets transfer small amounts repeatedly to hide origins.

3. Rug Pulls

Developers drain liquidity by removing token pools.

4. Market Manipulation

Fake transaction volume or wash trading to inflate token value.

5. Flash Loan Exploits

Large short-term loans are used to alter token prices.

6. Contract Exploitation

Vulnerable smart contracts allow unauthorized withdrawals.

These threats cannot be identified without analyzing wallet-to-wallet relationships over time.

4.3 Security Analysis Approach in the Proposed System

The proposed model introduces a multi-stage security auditing mechanism:

Stage-1: Monitoring Transaction Behavior

System monitors:

- Number of incoming vs outgoing transactions
- Sudden variations in token flow
- Interaction frequency with risky nodes
- A deviation from normal wallet behavior raises suspicion.

Stage-2: Graph-Based Structural Analysis

Using graph representation:

- Centrality measures identify dominant or abnormal nodes
- Multi-hop relationships detect laundering chains
- Dense sub-graphs reveal coordinated wallets
- Path similarity measures detect repeated movement traces

Fraud wallets often follow patterns:

- Star-shaped flow (money-receiver center)
- Cyclic transfers (wash laundering)
- Sudden high-value outbound transfers

Stage-3: Embedding-Based Risk Scoring

Graph embeddings convert relational structure into numeric vectors.

Wallet scoring is based on:

- Similarity with known fraud nodes
- Cluster closeness
- Outlier distance
- Higher risk score → wallet more likely fraudulent.

Stage-4: ML-Driven Classification Using GNNs

GNN models learn representations and assign a fraud probability.

GNN decisions consider:

- Neighborhood behavior
- Transaction timing
- Relationship strength
- Structural influence

The output is:

- **Fraudulent**
- **Legitimate**
- **Likely-fraud (at-risk)**

Stage-5: Alert Generation and Auditing

When high-risk wallets are detected:

- The system flags suspicious addresses
- Alerts analysts for manual review
- Risk tags remain stored for future matching
- Historic transaction paths can be traced

4.4 Auditing Mechanism Workflow

The auditing mechanism follows this cycle:

Figure 3:

Additionally:

- Stored audit logs allow forensic tracing
- Graph visualization supports investigation
- Users can track wallet evolution across time.

4.5 Features of Proposed Auditing Mechanism

Table :2

Auditing Feature	Description
Continuous Monitoring	Real-time analysis of wallet behavior
Historical Tracing	Previous suspicious interactions can be revisited
Risk Scoring Layer	Classifies low-risk vs high-risk wallets
Pattern Visualization	Graph structures reveal laundering paths
Auto-Flagging	Alerts when pattern threshold exceeds normal range

4.6 Evaluation in Security Context

The security mechanism is evaluated using:

- **Recall**
- **Precision**
- **ROC-AUC**
- **False-Positive and False-Negative Analysis**

4.7 Security Improvements Achieved

With the proposed model:

- Fraud detection becomes automated
- Detection happens before major loss
- Multiple wallet links are analyzed
- Hidden laundering networks become visible
- GNN improves early detection accuracy

Moreover, repeated patterns are learned automatically and continuously.

4.8 Limitations and Challenges

Although highly effective, some limitations exist:

- Lack of real identity for tied wallets
- Continuous updates needed for live blockchain tracking
- Computational cost rises for large networks
- Smart contract fraud not fully captured

Future work can incorporate:

- Hybrid identity-based detection
- Smart contract code auditing
- Real-time streaming GNNs

Chapter 5

Experimental Evaluation and Results(progressive)

This chapter presents the experimental setup, evaluation strategy, performance metrics, and results obtained from the proposed fraud detection system based on graph embeddings and Graph Neural Networks (GNNs).

5.1 Experimental Setup

For evaluation, the dataset was converted into a transactional graph where:

- Nodes = Wallets (unique addresses)
- Edges = Transactions (directed transfers)

Graph-based embeddings (Node2Vec / GraphSAGE) were generated, followed by GNN-based classification.

Hardware Used

- CPU: Intel i5/ Ryzen equivalent
- RAM: 8–16 GB
- GPU (optional): NVIDIA CUDA support

Software Used

- Python
- NetworkX
- PyTorch-Geometric
- Pandas & NumPy
- Matplotlib

5.2 Dataset Split

The dataset was divided into:

- **70%** Training
- **15%** Validation
- **15%** Testing

This method allows unbiased evaluation.

5.3 Evaluation Metrics

Performance was measured using standard ML classification parameters:

1. Accuracy:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- TP = True Positive
- FP = False Positive
- TN = True Negative
- FN = False Negative

Accuracy shows overall correctness.

2. Precision:

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

3.Recall (Sensitivity):

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

4. F1 Score:

$$F1 = 2 \times \frac{Precision \cdot Recall}{Precision + Recall}$$

5. AUC Score:

- Area under ROC curve represents model stability across thresholds.
- AUC close to **1.0** indicates robust detection.

5.4 Experimental Outcomes

From the evaluation:

- Proposed GAT-GNN provides highest accuracy
- Embeddings improved separability between fraud vs genuine nodes

6. Results (Progressive):

- Data Acquisition and Cleaning - 80% : We have successfully accessed and downloaded the raw transaction data, specifically focusing on the interactions within key DeFi protocols like Uniswap/Aave. 80% of the cleaning process is done—this involved normalizing address formats, handling missing values, and filtering out non-essential system transactions. We are confident in the quality of the data going into the next stage.

- Complete Transaction Graph Construction - 50% : Our progress here is solid. We have successfully modeled the initial dataset into a graph structure where addresses are nodes and transactions are directed edges. The core challenge has been ensuring efficient graph storage and indexing for high-speed access. We are at the stage of finalizing the massive graph object, which is why we mark this at 50% completion.

- Complete Initial Feature Engineering - 30% : We have defined and extracted a robust set of initial features. This includes crucial node features like activity frequency, balance changes, and contract interaction patterns, as well as edge features like transaction value. 80% of feature extraction is automated and complete. The remaining 30% involves deriving more complex, higher-order temporal features which will be optimized during the GNN training phase.

7. References:

1. Adams, Hayden. “UniSwap.” 2018 https://hackmd.io/@HaydenAdams/HJ9jLsfTz.

2. Buterin, Vitalik. “A Next-Generation Smart Contract and Decentralized Application Platform.” 2013; https://ethereum.org/en/whitepaper/.

3. Ashfaq, T., Khalid, R., Yahaya, A. S., Aslam, S., Azar, A. T., Alsafari, S., & Hameed, I. A. (2022). *A Machine Learning and Blockchain Based Efficient Fraud Detection Mechanism*. *Sensors*, 22(19), 7162.

4. Gao, P., Li, Z., Zhou, D., & Zhang, L. (2024). *Reinforced Cost-Sensitive Graph Network for Detecting Fraud Leaders in Telecom Fraud*. *Journal of Electrical Systems*, 20(10s).

5. Hasan, M., Rahman, M. S., Janicke, H., & Sarker, I. H. (2024). Detecting anomalies in blockchain transactions using machine learning classifiers and explainability analysis. Blockchain: Research and Applications, 5(3), 100207. https://in.docworkspace.com/d/sIEHcgrhn8InKyQY?sa=601.1037

6. Iftekhar Rasul1 , S M Iftekhar Shaboj2 , Mainuddin Adel Rafi3 , Md Kauser Miah4 , Md Redwanul Islam5 , Abir Ahmed https://in.docworkspace.com/d/sIP_cgrhnxYnKyQY?sa=601.1037