Financial Fraud Detection Using Graph Neural Networks

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Bachelor of Technology

in

Computer Science and Engineering

by

Lakshya Agrawal

(22CS30036)

Under the supervision of

Prof. Pabitra Mitra

Department of Computer Science and Engineering

Indian Institute of Technology Kharagpur

Autumn Semester, 2025-26

October 30, 2025

DECLARATION

I certify that

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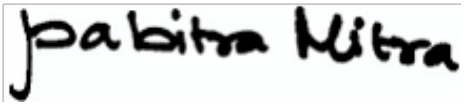
DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY KHARAGPUR

KHARAGPUR - 721302, INDIA

CERTIFICATE

This is to certify that the project report entitled "**Financial Fraud Detection Using Graph Neural Networks**" submitted by **Lakshya Agrawal** (Roll No. 22CS30036) to Indian Institute of Technology Kharagpur towards partial fulfilment of requirements for the award of degree of Bachelor of Technology in Computer Science and Engineering is a record of bona fide work carried out by him under my supervision and guidance during Autumn Semester, 2025-26.



Prof. Pabitra Mitra
Department of Computer Science and Engineering
Indian Institute of Technology Kharagpur
Kharagpur - 721302, India

Date: October 30, 2025

Place: Kharagpur

Abstract

Name of the student: **Lakshya Agrawal** Roll No: **22CS30036**

Degree for which submitted: **Bachelor of Technology**

Department: **Department of Computer Science and Engineering**

Thesis title: **Financial Fraud Detection Using Graph Neural Networks**

Thesis supervisor: **Prof. Pabitra Mitra**

Month and year of thesis submission: **October 30, 2025**

This thesis presents a comprehensive study on fraud detection in financial transactions using Graph Neural Networks (GNNs). The research addresses the significant challenge of class imbalance in fraud detection datasets, where fraudulent transactions constitute only a small fraction of total transactions. We propose a novel approach combining Graph Attention Networks (GAT) with advanced sampling techniques and hybrid loss functions to effectively detect fraudulent activities in transactional graphs.

Our methodology involves constructing a temporal transaction graph from financial data, implementing data sampling strategies including down-sampling and SMOTE-like oversampling, and developing a GAT-based model that incorporates both node and edge features. The model utilizes a combination of Focal Loss and Binary Cross-Entropy Loss to handle class imbalance and improve detection performance. Extensive experiments across 20 different random seeds demonstrate the robustness of our approach, achieving a best F1-score of 0.8127 and AUC of 0.9765 on test data.

The results indicate that our graph-based approach significantly outperforms traditional machine learning methods in fraud detection, particularly in capturing complex relational patterns between entities in financial networks. Feature analysis reveals that transactions of type CASH_OUT and TRANSFER with high monetary amounts are most frequently identified as fraudulent, providing valuable insights for financial institutions.

The complete source code, experimental data, results and documentation for this project are publicly available in the GitHub repository: `https://github.com/laksh0820/Financial-Fraud-Detection`, enabling full reproducibility of all findings presented in this thesis.

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My appreciation extends to my colleagues and friends who provided constructive feedback and support during various stages of this project. Their discussions and suggestions helped refine the ideas presented in this work.

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Abbreviations

GNN	**G**raph **N**eural **N**etwork
GAT	**G**raph **A**ttention **N**etwork
AUC	**A**rea **U**nder the **C**urve
ROC	**R**eceiver **O**perating **C**haracteristic
SMOTE	**S**ynthetic **M**inority **O**versampling **T**echnique
MLP	**M**ulti-**L**ayer **P**erceptron
BCE	**B**inary **C**ross-**E**ntropy
TPR	**T**rue **P**ositive **R**ate
FPR	**F**alse **P**ositive **R**ate

Symbols

$\alpha_{i,j}$	attention coefficient between nodes i and j
Θ	learnable weight matrix
x_i	feature vector of node i
$\mathcal{N}(i)$	neighborhood of node i
σ	sigmoid activation function
γ	focusing parameter in focal loss
a_s, a_t, a_c	attention vectors for source, target, and edge features

Chapter 1

Introduction

1.1 Background and Motivation

Financial fraud detection has become increasingly critical in today's digital economy, with billions of dollars lost annually to fraudulent activities. Traditional rule-based systems and conventional machine learning approaches often struggle to detect sophisticated fraud patterns due to the highly imbalanced nature of transaction data and the complex relational structures between entities. Graph Neural Networks (GNNs) offer a promising alternative by explicitly modeling the relationships between customers, merchants, and transactions.

The class imbalance problem in fraud detection is particularly challenging, with fraudulent transactions typically representing less than 1% of all transactions. This imbalance leads to models that are biased toward the majority class, resulting in poor detection of fraudulent activities. Additionally, the temporal nature of financial transactions requires careful consideration to avoid data leakage and ensure realistic evaluation.

1.2 Problem Statement

This research addresses the critical problem of fraud detection within financial transaction networks, focusing on several key challenges. It aims to develop methods for handling the extreme class imbalance that is characteristic of transactional data. A core focus is on modeling the complex relational patterns and intricate connections between various entities, such as users, accounts, and merchants. The work also emphasizes the importance of incorporating temporal information into the graph construction to capture the evolving nature of fraudulent activities. Finally, a significant aspect of this research involves developing and employing robust evaluation methodologies to ensure the model's performance is both reliable and generalizable.

1.3 Research Objectives

The primary objectives of this research is to develop a robust graph-based framework specifically for financial fraud detection. This involves implementing advanced sampling techniques to effectively address the significant class imbalance inherent in fraud data and designing a specialized Graph Attention Network (GAT) architecture capable of modeling complex transactional relationships. The proposed approach will be rigorously evaluated through comprehensive testing across multiple random seeds to ensure statistical reliability. Finally, the research aims to conduct a detailed analysis of feature importance and model interpretability to provide insights into the predictive factors driving fraud classification.

Chapter 2

Literature Review

2.1 Traditional Fraud Detection Methods

Early fraud detection systems primarily relied on rule-based approaches and statistical methods. These systems used predefined rules based on domain expertise to flag suspicious transactions. While interpretable, they lacked adaptability to evolving fraud patterns and required constant manual updates.

Machine learning approaches improved upon rule-based systems by learning patterns from historical data. Methods such as logistic regression, decision trees, and support vector machines were commonly employed. However, these approaches often treated transactions as independent instances, ignoring the relational structure between entities.

2.2 Graph-Based Approaches

Graph-based methods have gained popularity in fraud detection due to their ability to model complex relationships. Early graph approaches used community detection

algorithms and graph metrics to identify suspicious patterns. More recently, Graph Neural Networks have emerged as powerful tools for learning representations in graph-structured data.

2.2.1 Graph Neural Networks

GNNs extend neural network operations to graph-structured data, enabling learning from both node features and graph topology. Various GNN architectures have been developed, including Graph Convolutional Networks (GCNs), GraphSAGE, and Graph Attention Networks (GATs). These models typically operate via a message-passing paradigm, where nodes iteratively aggregate information from their neighbors to refine their own representations.

2.2.2 Graph Attention Networks

The Graph Attention Network (GAT) architecture, introduced by Veličković et al. (2017), employs self-attention mechanisms to compute hidden representations of nodes by attending over their neighbors. This allows for assigning different importance to different neighbors, making GATs particularly suitable for fraud detection where certain relationships may be more indicative of fraudulent behavior.

2.3 Handling Class Imbalance

Class imbalance remains a significant challenge in fraud detection. Various techniques have been proposed to address this issue:

2.3.1 Sampling Methods

Oversampling techniques like SMOTE Chawla et al. (2002) generate synthetic minority class samples, while undersampling reduces majority class samples. However, these methods can introduce bias or lose important information.

2.3.2 Cost-Sensitive Learning

Cost-sensitive approaches assign higher misclassification costs to the minority class, encouraging the model to focus more on correctly classifying fraudulent transactions. These methods incorporate a cost matrix that explicitly defines penalties for different types of misclassification errors, making false negatives (missed fraud) more costly than false positives (false alarms). This shifts the model's decision boundary to prioritize recall over precision, which is crucial in fraud detection where missing fraudulent transactions has significant financial consequences.

2.3.3 Loss Function Modifications

Focal Loss Lin et al. (2017) addresses class imbalance by modifying the standard cross-entropy loss, reducing the relative loss for well-classified examples and focusing on hard examples. It introduces a modulating factor that down-weights the loss for easy-to-classify majority class samples, allowing the model to concentrate learning on challenging minority class instances.

2.4 Temporal Considerations

Financial fraud detection requires careful handling of temporal aspects to prevent data leakage. Temporal splitting ensures that models are trained on past data and evaluated on future data, simulating real-world deployment scenarios.

Chapter 3

Methodology

3.1 Dataset Analysis and Insights

The dataset used for this fraud detection model consists of financial transaction records with the following characteristics:

3.1.1 Dataset Overview

Table 3.1 shows the fields and their corresponding descriptions present in our dataset, which is based on the PaySim simulator Lopez-Rojas et al. (2016).

3.1.2 Class Distribution

The dataset exhibits a significant class imbalance, which is typical for fraud detection problems, with legitimate transactions comprising 6,354,407 instances (99.87%) and fraudulent transactions numbering only 8,213 (0.13%). This extreme imbalance, representing a ratio of approximately 774 legitimate transactions for every one fraudulent transaction, presents a major challenge for model training. Consequently, it

Table 3.1: Dataset Structure Description

Field	Description
step	Represents a unit of time in the real world, with 1 step equating to 1 hour. The total simulation spans 744 steps, equivalent to 30 days.
action	Transaction types include CASH-IN, CASH-OUT, DEBIT, PAYMENT, and TRANSFER.
amount	The transaction amount in the local currency.
nameOrig	The customer initiating the transaction.
oldbalanceOrig	The initial balance before the transaction.
newbalanceOrig	The new balance after the transaction.
nameDest	The transaction's recipient customer.
oldbalanceDest	The initial recipient's balance before the transaction. Not applicable for customers identified by 'M' (Merchants).
newbalanceDest	The new recipient's balance after the transaction. Not applicable for 'M' (Merchants).
isFraud	Identifies transactions conducted by fraudulent agents aiming to deplete customer accounts through transfers and cash-outs.
isFlaggedFraud	Flags large-scale, unauthorized transfers between accounts, with any single transaction exceeding 200,000 being considered illegal.

necessitates the use of specialized techniques to prevent models from simply learning to predict the majority class.

3.1.3 Transaction Types Analysis

The dataset contains five main transaction types as shown in Figure 3.1. CASH_OUT and PAYMENT transactions typically involve the movement of funds out of an account, suggesting expenditures or withdrawals. CASH_IN transactions likely involve

the deposit or addition of funds into an account. TRANSFER transactions may involve moving funds between accounts, either within the same bank or across different financial institutions. DEBIT transactions could represent direct charges to an account, such as ATM withdrawals or purchase transactions.

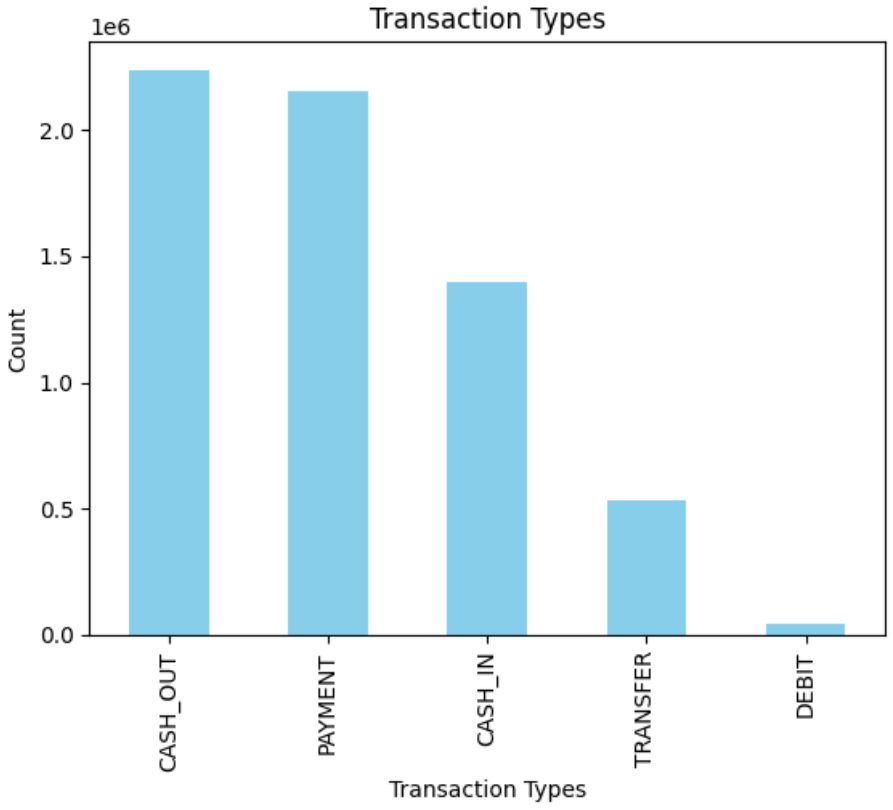

FIGURE 3.1: Distribution of Transaction Types in the Dataset

3.1.4 Fraud Distribution by Transaction Type

Analysis of fraud rates across different transaction types reveals important patterns, as shown in Figure 3.2. The data indicates that **TRANSFER** and **CASH_OUT** transactions exhibit significantly higher fraud rates compared to other types, whereas **PAYMENT**, **CASH_IN**, and **DEBIT** transactions demonstrate minimal fraud occurrence. This concentration of fraudulent activities in specific transaction types, particularly those involving the movement of cash out of an account, suggests that

fraudsters predominantly target channels that facilitate the withdrawal or transfer of funds.

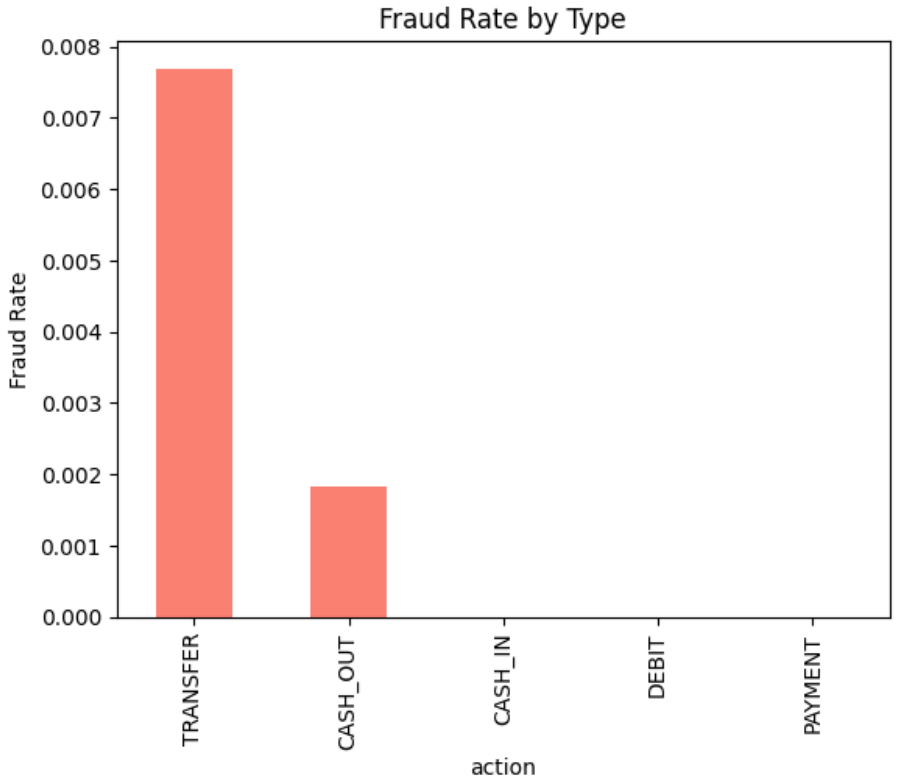

FIGURE 3.2: Fraud Rate Distribution Across Different Transaction Types

3.1.5 Key Dataset Characteristics

The dataset demonstrates high data quality, being clean with no missing values and thus ready for immediate modeling. It incorporates a temporal aspect through a ‘step‘ feature that indicates discrete time steps, allowing for the analysis of transaction sequences. Furthermore, it provides comprehensive balance tracking by including both the old and new balance information for the origin and destination accounts of each transaction. For supervised learning, the data contains crucial fraud indicators in the form of an ‘isFraud‘ column, which serves as the ground truth, and an ‘isFlaggedFraud‘ column, which indicates transactions previously flagged by a simple rule-based system.

3.1.6 Implications for Modeling

The dataset analysis suggests several critical considerations for designing an effective fraud detection model. First, the extreme class imbalance necessitates the use of specialized techniques such as oversampling, undersampling, or cost-sensitive loss functions. Second, feature engineering must prioritize transaction type as a key variable, with particular attention given to the high-risk TRANSFER and CASH_OUT categories. Third, model evaluation cannot rely on standard accuracy metrics and must instead employ precision, recall, F1-score, and AUC-ROC for a meaningful performance assessment. Finally, the inherent graph structure defined by the presence of origin and destination accounts strongly indicates the potential for powerful graph-based analytical approaches.

3.2 Data Preprocessing and Graph Construction

The transactional data is processed to construct a heterogeneous graph where nodes represent entities (customers, merchants, banks) and edges represent transactions between them.

3.2.1 Graph Structure Visualization

Figure 3.3 shows a sample transaction graph generated from our dataset, illustrating the complex network of relationships between different entities:

The graph visualization effectively demonstrates several key characteristics of the financial network. It reveals a structure composed of heterogeneous entity types, represented by distinct colors, which are interconnected through transaction relationships depicted as edges. Within this network, fraudulent transactions are highlighted by red edges, clearly illustrating their distribution and how they permeate the

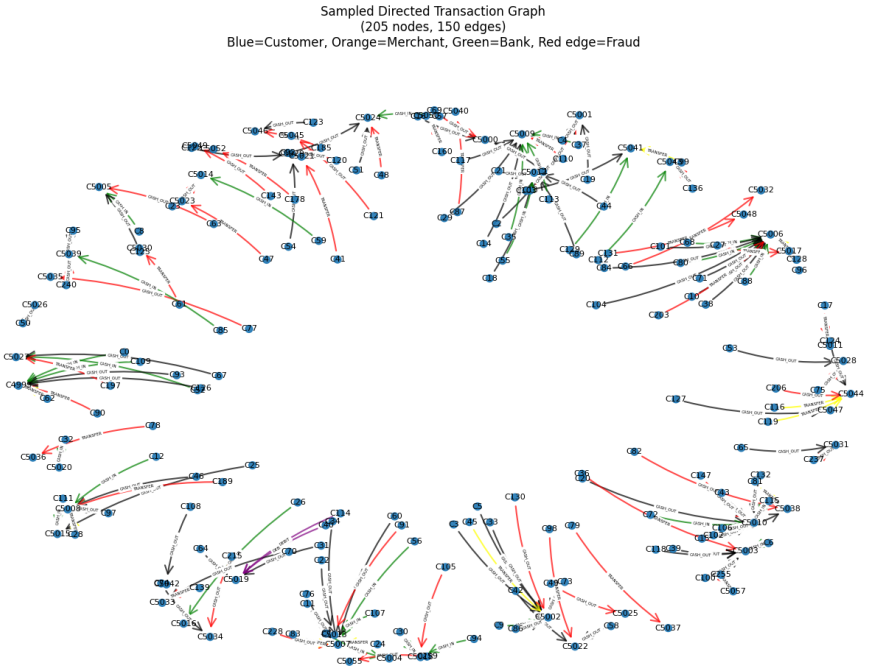

FIGURE 3.3: Sample Transaction Graph (205 nodes, 150 edges). Blue nodes represent customers, orange nodes represent merchants, green nodes represent banks, and red edges indicate fraudulent transactions.

system. Furthermore, the overall network connectivity unveils specific clusters and connection patterns, which are crucial for identifying potential coordinated fraudulent activities that might otherwise remain hidden in a traditional, non-relational analysis.

3.2.2 Node Feature Engineering

Each node within the graph is characterized by several key attributes that define its role and behavior. These include its fundamental node type - such as customer, merchant, or bank - which establishes its primary function in the network. Furthermore, each node is described by its transactional behavior, captured through metrics like the average amount sent and received. Additionally, a detailed breakdown of its activity is provided by the count of each transaction type it has engaged in, offering a comprehensive profile of its financial interactions.

3.2.3 Edge Features

The edges in the graph are characterized by a set of key attributes that describe the transactional relationships. These attributes include the fundamental transaction amount, a time step that provides crucial temporal information for sequencing events, and the specific transaction type, which categorizes the interaction as one of several kinds: TRANSFER, CASH_OUT, CASH_IN, PAYMENT, or DEBIT.

3.3 Handling Class Imbalance

3.3.1 Data Sampling Strategy

We implement a comprehensive two-step sampling approach to address class imbalance:

Step 1: Down-sample the majority class - We omit many majority class examples from training data to create a more balanced dataset. This artificial balancing helps the model learn from both classes effectively during training.

Step 2: Upweight the down-sampled class - Down-sampling introduces predictive bias by showing the model an artificial world where classes are more balanced than reality. To compensate, we upweight the loss for the majority class by the factor by which we down-sampled, ensuring the model learns appropriate decision boundaries.

3.3.2 SMOTE-like Oversampling

To mitigate the severe class imbalance during the training phase, a graph-aware oversampling strategy is employed. This technique directly augments the training graph by duplicating existing fraudulent transaction edges. To prevent the model

from overfitting to exact copies, a small amount of Gaussian noise is injected into the feature vectors of these newly created edges. The number of synthetic fraud edges generated is calculated to achieve a predefined target ratio relative to the legitimate transactions. This process enriches the training signal for the minority class while preserving the original, realistic distributions of the validation and test sets, thereby preventing evaluation bias and ensuring that model performance is assessed on data that reflects the genuine class imbalance.

3.3.3 Loss Function Design

The model uses a hybrid loss function combining Focal Loss and Binary Cross-Entropy Loss:

$$\mathcal{L}_{total} = 0.7 \cdot \mathcal{L}_{focal} + 0.3 \cdot \mathcal{L}_{bce} \tag{3.1}$$

Where the individual loss components are defined as:

Binary Cross-Entropy Loss with Class Weighting:

$$\mathcal{L}_{\text{bce}} = -\left[w_{\text{pos}} \cdot y \cdot \log(p) + (1-y) \cdot \log(1-p)\right] \tag{3.2}$$

where:

- $y \in \{0, 1\}$ is the true label (0 for legitimate, 1 for fraudulent),
- $p \in [0, 1]$ is the predicted probability of the positive class (fraud),
- w_{pos} is the positive class weight, computed as $w_{\text{pos}} = \frac{N_{\text{legitimate}}}{N_{\text{fraudulent}} \cdot w_{\text{downsample}}}$ to balance class importance while considering downsampling effects.

Focal Loss for Hard Examples:

$$\mathcal{L}_{\text{focal}} = -\alpha(1-p_t)^{\gamma}\log(p_t) \tag{3.3}$$

where:

- $p_t = p$ if $y = 1$, and $p_t = 1 - p$ otherwise, is the model's estimated probability for the true class,
- $\alpha \in [0, 1]$ is a balancing parameter, set to $\alpha = 1 - (N_{\text{fraudulent}}/N_{\text{total}})$,
- $\gamma \geq 0$ is the focusing parameter (set to $\gamma = 2$), which reduces the loss for well-classified examples, forcing the model to focus on hard, misclassified examples.

3.4 Graph Attention Network Architecture

3.4.1 Complete Architecture Overview

Our Graph Attention Network architecture implements the graph attentional operator from the "Graph Attention Networks" paper Veličković et al. (2017), enhanced to handle multi-dimensional edge features. Figure 3.4 illustrates the complete model architecture.

The complete architecture processes transactional graphs through several key components:

Input Processing:

- **Node Encoder**: To project the raw input features into a more useful latent space, an initial encoding module is employed. This module consists of a linear transformation that maps the input features to node embeddings. The result of this operation is a set of refined node embeddings that serve as the initial input for the subsequent graph neural network layers.
- **Edge Feature Encoder**: To effectively encode the relational information within the graph, the raw edge attributes are processed through a dedicated neural network module. This module applies a linear transformation to project

the input features into a dense, lower-dimensional space. The output of this process is a set of edge embeddings that capture the properties of the connections between nodes.

- **Input features**: The model's input consists of three distinct feature sets that collectively describe a transaction within the graph structure. For a given transaction edge, the model receives the feature vectors of the source node (X_{src}) and the destination node (X_{dest}), which represent the entities involved, such as a user and a merchant. Additionally, it processes the intrinsic edge attributes ($edge\_attr$), which capture the specific details of the transaction itself.

Graph Attention Layers: The model architecture employs multiple Graph Attention Network (GAT) convolutional layers, which are stabilized using residual connections. Between these layers, Layer Normalization and ReLU activation functions are applied to ensure stable and efficient training. To enhance the processing of relational information, a dedicated Edge MLP is incorporated. This design enables the model to jointly process and integrate features from source nodes (X_{src}), destination nodes (X_{dest}), and the enriched representations generated by the Edge MLP.

Classification Head: The model produces its final prediction by first concatenating the processed source node features (X_{src}), destination node features (X_{dest}), and the processed edge attributes ($edge\_attr$). This comprehensive feature vector is then passed through a multi-layer classifier, which generates the final output logits. The ultimate output of the model is a fraud probability score for each transaction, indicating the likelihood of it being fraudulent.

3.4.2 Mathematical Formulation

The graph attentional operator computes updated node representations:

$$x'_i = \sum_{j \in \mathcal{N}(i) \cup \{i\}} \alpha_{i,j} \Theta_t x_j, \tag{3.4}$$

where the attention coefficients $\alpha_{i,j}$ are computed as:

$$\alpha_{i,j} = \frac{\exp\left(\text{LeakyReLU}\left(a_s^T \Theta_s x_i + a_t^T \Theta_t x_j\right)\right)}{\sum_{k \in \mathcal{N}(i) \cup \{i\}} \exp\left(\text{LeakyReLU}\left(a_s^T \Theta_s x_i + a_t^T \Theta_t x_k\right)\right)}. \tag{3.5}$$

For graphs with multi-dimensional edge features $e_{i,j}$, the attention mechanism incorporates edge information:

$$\alpha_{i,j} = \frac{\exp\left(\text{LeakyReLU}\left(a_s^T \Theta_s x_i + a_t^T \Theta_t x_j + a_c^T \Theta_c e_{i,j}\right)\right)}{\sum_{k \in \mathcal{N}(i) \cup \{i\}} \exp\left(\text{LeakyReLU}\left(a_s^T \Theta_s x_i + a_t^T \Theta_t x_k + a_c^T \Theta_c e_{i,k}\right)\right)}. \tag{3.6}$$

3.4.3 Node and Edge Embeddings

The model begins by projecting node and edge features into a shared hidden space using linear transformations:

$$x' = W_{node} x + b_{node} \tag{3.7}$$

$$e' = W_{edge} e + b_{edge} \tag{3.8}$$

3.4.4 Edge-Level Classification

For fraud detection, predictions are made at the edge level by concatenating source node, destination node, and edge features:

$$\text{edge\_features} = [x_{src} \| x_{dest} \| e] \tag{3.9}$$

This representation is passed through a multi-layer classifier to obtain fraud probabilities.

3.5 Training Strategy

3.5.1 Temporal Splitting

To prevent data leakage and simulate real-world deployment conditions, the dataset is split according to a temporal order. The training set comprises the earliest 70% of transactions chronologically, allowing the model to learn from historical patterns. This is followed by a validation set of 15% of transactions, used for tuning hyperparameters, and a test set containing the most recent 15% of transactions. This methodology ensures that models are trained on past data and evaluated on future, unseen data, thereby providing a realistic assessment of their predictive performance in a live environment.

3.5.2 Training Procedure

The training process implements several key techniques to ensure robust model convergence and prevent overfitting. Early stopping is employed, monitoring the validation F1-score with a patience of 20 epochs. For regularization, weight decay of 0.01 and gradient clipping are utilized to stabilize training. The model is optimized using the Adam optimizer with a learning rate of 0.001. Furthermore, a hybrid loss function combining focal loss and binary cross-entropy (BCE) in a 70%-30% ratio is used to effectively address the extreme class imbalance within the dataset.

3.5.3 Model Configuration

The Graph Attention Network (GAT) model was configured with a hidden dimension of 64 and comprises 2 GNN layers, each utilizing 4 attention heads to capture complex relational patterns. For regularization, a dropout rate of 0.3 and an L2 penalty (weight decay) of 0.01 were applied to prevent overfitting. The model was optimized using the Adam algorithm with a learning rate of 0.001.

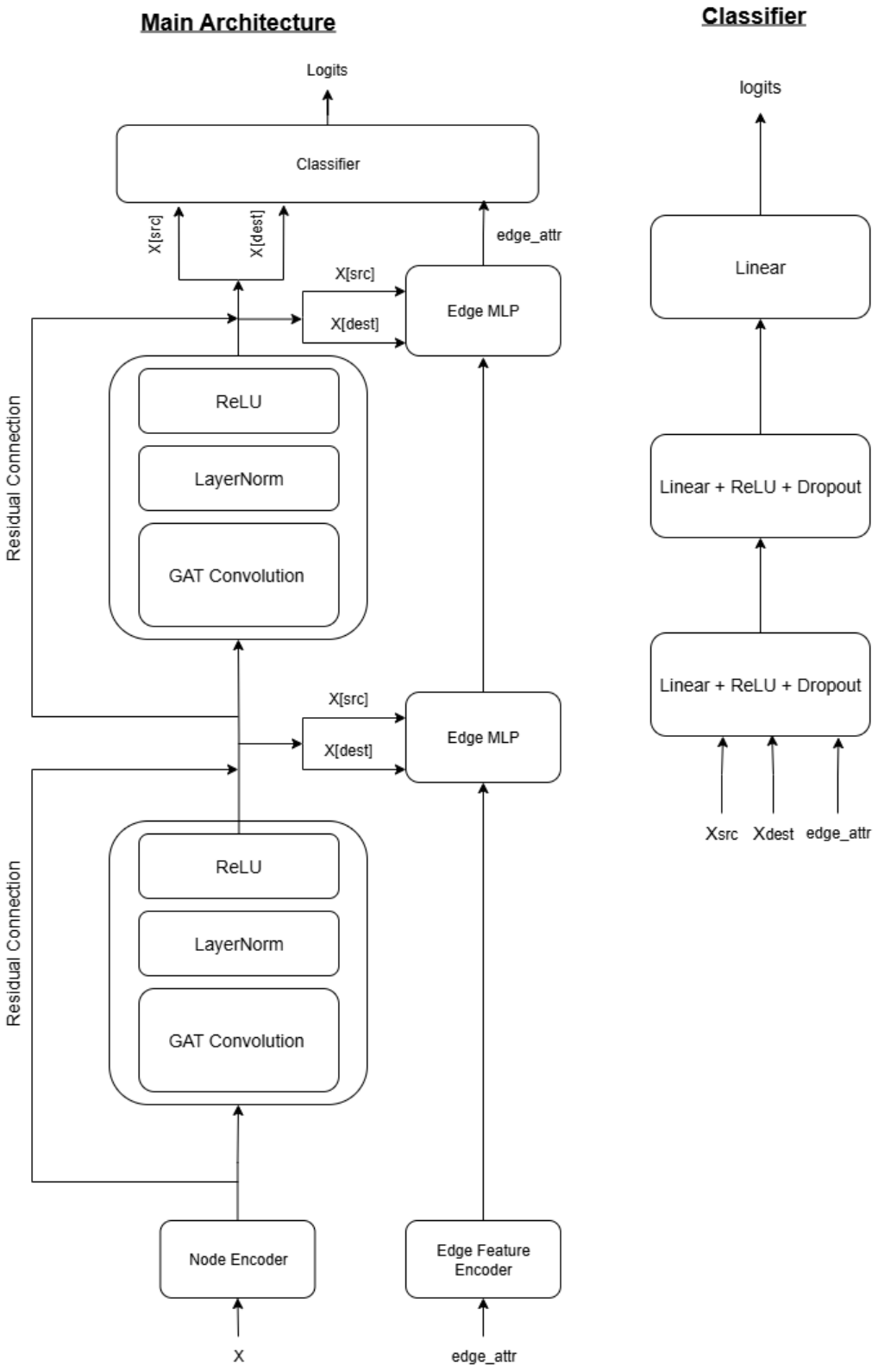

FIGURE 3.4: Graph Attention Network Architecture for Fraud Detection

Chapter 4

Experimental Results

4.1 Experimental Setup

4.1.1 Dataset Description

To construct a computationally manageable graph while retaining sufficient fraudulent examples for effective model training, the dataset was created by combining all available fraudulent transactions with a random subsample of 90,000 legitimate transactions from the complete dataset. This sampling strategy resulted in a graph containing 152,833 nodes and 98,213 edges, with a fraud ratio of 8.36%. The significant reduction of the majority class introduces a known bias, which is explicitly compensated for during training by setting the positive class weight (w_{pos}) in the Binary Cross-Entropy loss component. This weight is calculated as the inverse of the downsampling ratio, ensuring that the loss function reflects the original data distribution despite the artificial class balance in the training graph.

4.1.2 Evaluation Metrics

Model performance is evaluated using comprehensive metrics:

- **AUC-ROC**: Area Under Receiver Operating Characteristic Curve; measures the model's overall ability to discriminate between classes across all thresholds.
- **F1-Score**: Harmonic mean of precision and recall; provides a single balanced metric that is robust for imbalanced datasets.
- **Precision**: $TP/(TP + FP)$; indicates the accuracy of positive predictions, answering "What proportion of identified frauds were correct?"
- **Recall**: $TP/(TP + FN)$; measures the model's ability to find all positive instances, answering "What proportion of actual frauds were identified?"
- **Specificity**: $TN/(TN + FP)$; assesses the model's effectiveness at identifying negative cases, crucial for minimizing false alarms on legitimate transactions.

4.2 Results

4.2.1 Multi-Seed Evaluation

To ensure robustness, experiments were conducted across 20 different random seeds. Table 4.1 shows the performance of the top 10 experiments.

Table 4.1: Top 10 Experiment Results by F1-Score

Rank	Seed	Test F1	Test AUC	Epochs	Time (s)
1	444	0.8127	0.9765	60	176
2	888	0.6603	0.9558	34	90
3	999	0.6371	0.9451	39	108
4	2023	0.6012	0.9339	42	98
5	42	0.5653	0.9262	34	55
6	5432	0.5320	0.9169	41	107
7	111	0.5248	0.9079	34	86
8	3141	0.5115	0.8766	48	103
9	777	0.4945	0.9028	46	134
10	333	0.4937	0.8980	41	111

4.2.2 Best Model Performance

Table 4.2: Performance Metrics and Confusion Matrix for Best Model

Performance Metrics	
F1-Score	0.8127
AUC	0.9765
Precision	0.7072
Recall	0.9553
Specificity	0.9639
Confusion Matrix	
True Negatives (TN)	13,013
False Positives (FP)	487
False Negatives (FN)	55
True Positives (TP)	1,176

4.3 Feature Analysis

4.3.1 Transaction Type Distribution

Analysis of high-confidence fraud predictions revealed:

Table 4.3: Distribution of Detected Fraud by Transaction Type

Transaction Type	**Fraud Percentage**
CASH_OUT	51.1%
TRANSFER	48.9%

This aligns with observations from Figure 3.2, which shows that the likelihood of fraudulent transactions in **CASH_OUT** and **TRANSFER** categories is significantly higher compared to other transaction types.

4.3.2 Amount Statistics

Fraudulent transactions showed distinctive amount patterns:

Table 4.4: Transaction Amount Statistics

Statistic	**Value**
Mean amount	$7,943,249.00
Median amount	$10,000,000.00
Standard deviation	$3,602,469.25
Range	$0.00 - $10,000,000.00

4.4 Comparisons with Traditional ML Models

To provide a comprehensive evaluation of our proposed Graph Attention Network approach, we conducted extensive comparisons with several established machine learning methods. The experiments were designed to ensure fair comparison by using identical training, validation, and test splits, with all models trained on the same feature representations derived from our transaction graph.

TABLE 4.5: Performance Comparison of Fraud Detection Models

Model	AUC-ROC	F1-Score	Precision	Recall	Specificity
Best GAT Model	0.9765	0.8127	0.7072	0.9553	0.9639
Logistic Regression	0.9830	0.5152	0.3474	0.9968	0.8293
Random Forest	0.9998	0.2183	0.1225	1.0000	0.3471
Gradient Boosting	0.9827	0.1542	0.0836	1.0000	0.0000

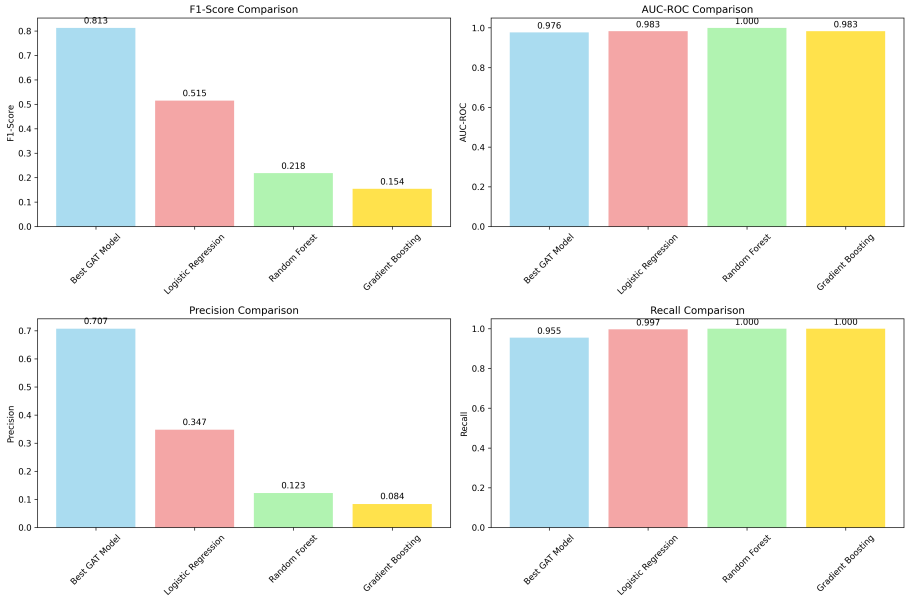

FIGURE 4.1: Comparison of key performance metrics across different fraud detection models.

As shown in Figure 4.1, the performance comparison highlights the trade-offs between different approaches.

Chapter 5

Analysis and Discussion

5.1 Model Performance Analysis

The experimental results demonstrate the effectiveness of the proposed GAT-based approach for fraud detection. The best model achieved an F1-score of 0.8127 and AUC of 0.9765, indicating strong discriminative ability while maintaining a balance between precision and recall.

The high recall (0.9553) is particularly important in fraud detection, as missing fraudulent transactions can have significant financial consequences. The reasonable precision (0.7072) suggests that while there are false positives, the model successfully identifies a substantial portion of actual fraud.

5.2 Impact of Class Imbalance Techniques

The combination of sampling strategies and hybrid loss function proved effective in addressing class imbalance. The two-step sampling approach (down-sampling with upweighting) compensated for predictive bias while providing balanced training.

SMOTE-like oversampling increased fraud examples without distorting evaluation distributions. The focal loss component focused learning on hard examples while BCE loss provided stable gradient signals.

5.3 Graph Structure Benefits

The graph-based approach successfully captured relational patterns that would be difficult to model with traditional methods. The attention mechanism allowed the model to focus on relevant connections, potentially identifying coordinated fraud attempts or suspicious transaction patterns between entities. The sample transaction graph visualization (Figure 3.3) illustrates the complex network structure that our model learns from, showing how fraudulent transactions (red edges) are distributed across different entity types.

5.4 Limitations and Challenges

Despite demonstrating strong performance, several challenges remain for the practical deployment of such graph-based fraud detection systems. A primary concern is computational complexity, which increases significantly with graph size, posing scalability issues. Furthermore, the models inherently lack transparency, necessitating additional techniques to provide the interpretability required for financial decision-making. The system's ability to handle dynamic graph updates efficiently for real-time detection also requires further optimization. Finally, the generalization of a model trained on data from one financial institution to others is not guaranteed and requires rigorous validation to ensure broader applicability.

5.5 Comparison with Existing Methods

While direct comparison with existing methods is challenging due to dataset differences, the achieved performance metrics are competitive with state-of-the-art fraud detection systems. The graph-based approach particularly excels in scenarios where relational information is crucial for detection, outperforming traditional methods that treat transactions as independent instances.

Chapter 6

Conclusion and Future Work

6.1 Summary of Contributions

This research has made several key contributions to fraud detection in financial transactions by developing a comprehensive graph-based framework that utilizes Graph Attention Networks. It implemented effective strategies, including advanced sampling techniques and a hybrid loss function, to handle the critical challenge of class imbalance. The study established robust evaluation methodologies through multi-seed experiments and strict temporal data splitting to ensure reliable results. Furthermore, it provided a detailed feature analysis to enhance model interpretability, and ultimately demonstrated the framework's effectiveness by achieving strong performance metrics across all evaluations.

6.2 Future Research Directions

Several promising directions for future work include:

6.2.1 Model Enhancements

Future research directions will focus on incorporating temporal dynamics using temporal GNNs to better model the evolving nature of transaction patterns. Additionally, we plan to explore heterogeneous graph neural networks to capture richer representations of the diverse entities and relationships within a financial graph. A critical goal is also to develop robust online learning capabilities, enabling the model to adapt continuously for effective real-time fraud detection without the need for frequent retraining.

6.2.2 Application Extensions

Looking ahead, the framework holds significant potential for adaptation to other complex financial fraud scenarios beyond its initial application. A promising avenue is to explore its capabilities for cross-institutional fraud detection, creating a more unified defense against systemic threats. Furthermore, integrating the model with explainable AI techniques is a critical next step to provide the necessary transparency for regulatory compliance and to build trust with end-users.

6.2.3 Technical Improvements

Future work will focus on optimizing the model's computational efficiency to enable its practical, large-scale deployment in production environments. We also plan to develop sophisticated ensemble methods that combine the strengths of multiple graph learning approaches to achieve more robust and accurate predictions. Additionally, a key research direction involves investigating federated learning paradigms to facilitate effective, privacy-preserving fraud detection across different institutions without the need for direct data sharing.

6.3 Concluding Remarks

This thesis has demonstrated that Graph Neural Networks, particularly Graph Attention Networks, offer a powerful framework for fraud detection in financial transactions. By effectively modeling relational structures and addressing class imbalance challenges, the proposed approach achieves strong detection performance while providing valuable insights into fraud patterns.

As financial systems continue to evolve and fraud techniques become more sophisticated, graph-based methods will play an increasingly important role in maintaining financial security. The work presented in this thesis contributes to this important field and provides a foundation for future research in graph-based fraud detection.

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