FraudGNN-RL: A Graph Neural Network with Reinforcement Learning for Adaptive Financial Fraud Detection

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ABSTRACT

Financial fraud, particularly in credit card transactions, contributes significantly to global economic losses, estimated at over $5.127 trillion annually. Traditional detection methods often fail to capture the evolving nature of fraudulent activities and the complex relationships within transaction networks. In this work, we propose *FraudGNN-RL*, a novel framework that integrates Graph Neural Networks (GNNs), Reinforcement Learning (RL), and Federated Learning (FL) to address these challenges on the Credit Card Fraud 2023 Dataset, which contains 550,000 transactions with a fraud rate of 0.172%. Our approach leverages a TSSGC architecture to model intricate transaction patterns, employs a Deep Q-Network (DQN) with Normalized Advantage Functions (NAF) for adaptive threshold adjustments, and uses FL to ensure privacy-preserving collaboration across institutions. Our Methods achieved an AUC-ROC of 0.9744, an AUC-PR of 0.8720, an F1 of 0.8957, and a Recall@5% of 0.9151, demonstrating superior performance compared to baselines while providing a robust, adaptive, and privacy-aware solution for modern Credit Card Fraud Detection.

KEYWORDS

Fraud Detection, Graph Neural Networks, Reinforcement Learning, Federated Learning, Credit Card Fraud

1 INTRODUCTION

Financial fraud remains a critical global issue, with annual losses exceeding $5.127 trillion as reported by the Association of Certified Fraud Examiners. Credit card fraud, in particular, has surged with the proliferation of digital payment systems, posing significant challenges to financial institutions. Traditional fraud detection methods, such as rule-based systems and static machine learning models, are often inadequate in capturing the complex, interconnected nature of financial transactions and adapting to rapidly evolving fraud patterns [5]. Moreover, the increasing emphasis on data privacy, driven by regulations like GDPR, demands solutions that can operate in a decentralized, privacy-preserving manner [8].

In this work, inspired by [4], we introduce *FraudGNN-RL*, a comprehensive framework that combines GNNs, RL, and FL to address these challenges. Our approach is specifically tailored to the Credit Card Fraud 2023 Dataset, which contains 550,000 transactions with a fraud rate of 0.172%, making it a highly imbalanced dataset that reflects real-world scenarios. The dataset's anonymized features (28 PCA components, transaction amount, and time) further complicate the task, requiring advanced techniques to extract meaningful patterns.

Our contributions are multifaceted:

- We propose a Temporal-Spatial-Semantic Graph Convolution (TSSGC) architecture to effectively model the temporal dynamics, spatial relationships, and semantic information within transaction networks.
- We develop an RL-based adaptive policy using a DQN with NAF, enabling dynamic adjustments to classification thresholds and feature weights in response to concept drift.
- We incorporate FL to facilitate privacy-preserving collaboration across multiple institutions, ensuring compliance with data privacy regulations.
- We conduct extensive experiments on the Credit Card Fraud 2023 Dataset, demonstrating significant improvements over state-of-the-art baselines such as GCN and GAT, with an AUC-ROC of 0.9744 and AUC-PR of 0.8720.

2 RELATED WORK

Fraud detection has evolved significantly over the years. Early methods relied on rule-based systems [2] and statistical techniques [3], which, while interpretable, lacked the ability to adapt to new fraud patterns. The advent of machine learning brought improvements, with models like logistic regression and random forests being applied to detect fraudulent transactions [12, 14]. However, these approaches often treat transactions as independent events, ignoring the inherent interconnectivity within financial networks.

Graph-based methods have emerged as a promising solution for modeling transaction relationships. Graph Convolutional Networks (GCNs) [7] and Graph Attention Networks (GATs) [13] have been used to capture spatial dependencies in transaction graphs [9]. Despite their success, these models typically operate in a static manner, failing to adapt to concept drift—a common challenge in fraud detection where fraud patterns evolve over time [8].

RL has shown potential in dynamic environments, such as financial trading [6], but its application in fraud detection remains limited. Recent studies have explored RL for adaptive threshold adjustment [8], yet integrating RL with graph-based models is underexplored. On the privacy front, FL has gained traction for enabling collaborative training without sharing raw data [10]. Works like [15] and [16] have applied FL to fraud detection, but they often lack the ability to model complex transaction graphs or adapt dynamically.

FraudGNN-RL bridges these gaps by integrating GNNs for graph modeling, RL for adaptability, and FL for privacy preservation, offering a comprehensive solution for Credit Card Fraud Detection.

3 METHODOLOGY

Figure 1 provides a visual overview of our proposed methodology, highlighting the integration of GNNs, RL, and FL in the fraud detection pipeline.

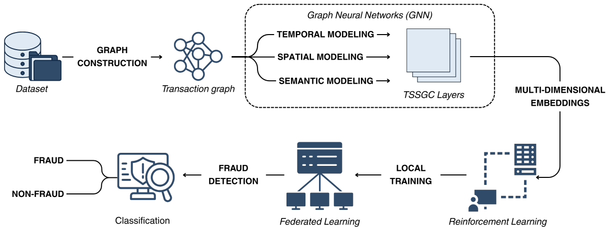


Figure 1: Federated GNN-Based Fraud Detection Pipeline with RL-Driven Adaptation

FraudGNN-RL is designed to address three key challenges in Credit Card Fraud Detection: capturing complex transaction patterns, adapting to evolving fraud tactics, and ensuring privacy-preserving collaboration. The framework consists of three main components: TSSGC, RL for adaptive detection, and FL for privacy preservation. Below, we provide a detailed explanation of each component and their integration.

3.1 Temporal-Spatial-Semantic Graph Convolution (TSSGC)

Financial transactions in the Credit Card Fraud 2023 Dataset are modeled as a heterogeneous graph $G = (V, E, X)$, where:

- V represents entities such as cardholders and merchants.
- E denotes transactions between entities, with each edge associated with a timestamp and transaction features (e.g., amount).
- X contains node feature vectors, which in this dataset include 28 PCA components, transaction amount, and time.

The TSSGC architecture is designed to capture three distinct aspects of the transaction graph:

- **Temporal Dynamics**: Transactions occur over time, and their patterns may evolve. We use a Gated Recurrent Unit (GRU) with a time-aware attention mechanism to model temporal dependencies. For a node v_i, the temporal embedding is computed as:

  $$\text{TEMP}(i) = \text{GRU}\left(\left\{(f_k, \alpha_k) \mid (v_i, v_j, t_k, f_k) \in E_i\right\}\right),$$

  where α_k is the attention weight based on the time difference:

  $$\alpha_k = \frac{\exp(-\beta(t_{\text{now}} - t_k))}{\sum_{(v_i, v_j, t_j, f_j) \in E_i} \exp(-\beta(t_{\text{now}} - t_j))},$$

  and β is a learnable decay parameter that controls the influence of past transactions.
- **Spatial Relationships**: Transactions form a network of interactions between entities. We employ a graph attention mechanism to aggregate information from neighboring nodes:

  $$\text{SPAT}(i) = \sum_{j \in \mathcal{N}(i)} \alpha_{ij} W_s h_j,$$

  where α_{ij} is computed using a LeakyReLU-based attention mechanism as described in [4], and W_s is a learnable weight matrix.
- **Semantic Information**: Different entities and transaction types carry semantic meaning (e.g., cardholder vs. merchant, transaction category). We use an embedding layer to encode this information:

  $$\text{SEM}(i) = W_m [h_i \parallel e_{\text{type}(i)}],$$

  where $e_{\text{type}(i)}$ is the type embedding for node v_i, and W_m is a learnable matrix.

The TSSGC layer combines these components to update node embeddings:

$$h_i^{(l+1)} = \sigma\left(W_t^{(l)} \cdot \text{TEMP}(i) + W_s^{(l)} \cdot \text{SPAT}(i) + W_m^{(l)} \cdot \text{SEM}(i) + b^{(l)}\right),$$

where σ is the ReLU activation function, and $W_t^{(l)}$, $W_s^{(l)}$, $W_m^{(l)}$, and $b^{(l)}$ are layer-specific parameters. We chose GCN over GAT or GIN for its computational efficiency and stability in federated settings, as noted in [4].

3.2 Reinforcement Learning for Adaptive Detection

Fraud patterns evolve over time, a phenomenon known as concept drift. To address this, we employ a DQN with NAF to learn an adaptive policy π for adjusting classification thresholds and feature weights. The RL setup is defined as follows:

- **State** s_t: The current graph embeddings generated by TSSGC layers at time t, capturing the state of the transaction network.
- **Action** a_t: Adjustments to the classification threshold and weights assigned to different features (e.g., emphasizing recent transactions over older ones).
- **Reward** r_t: A function that balances the true positive rate (TPR) and false positive rate (FPR), defined as:

  $$r_t = \text{TPR} - \lambda \cdot \text{FPR},$$

  where λ is a hyperparameter controlling the trade-off between detecting frauds and minimizing false positives.

The DQN is trained to minimize the temporal-difference loss:

$$L(\theta) = \mathbb{E}_{(s,a,r,s') \sim D}\left[\left(r + \gamma \max_{a'} Q(s', a'; \theta^-) - Q(s, a; \theta)\right)^2\right],$$

where D is a replay buffer storing past experiences, γ is the discount factor, and θ^- represents the parameters of a target network that stabilizes training [11]. The use of NAF ensures efficient exploration in continuous action spaces, allowing for fine-grained adjustments to thresholds and weights.

3.3 Federated Learning for Privacy Preservation

Given the sensitive nature of financial data, privacy preservation is a critical requirement. We adopt the Federated Averaging (FedAvg) algorithm [10] to enable collaborative training across multiple institutions without sharing raw data. Each institution k trains a local model M on its subset of the Credit Card Fraud 2023 Dataset, D_k, producing updated parameters w_k. The central server aggregates these parameters to update the global model:

$$w_{\text{global}} = \sum_k \frac{|D_k|}{\sum_j |D_j|} w_k.$$

This approach ensures that only model updates are shared, preserving the privacy of individual transactions while allowing the global model to benefit from diverse data sources.

3.4 Fraud Detection Pipeline

The FraudGNN-RL pipeline integrates the above components into a cohesive workflow, as illustrated in Figure 1:

- **Graph Construction and Update**: The transaction graph G is constructed from the Credit Card Fraud 2023 Dataset and updated with new transactions in real-time.
- **Embedding Generation**: TSSGC layers process the graph to generate node embeddings that capture temporal, spatial, and semantic information.
- **Action Selection**: The RL agent, using the DQN, selects actions (e.g., threshold adjustments) based on the current state (graph embeddings).
- **Transaction Classification**: Transactions are classified as fraudulent or legitimate using the embeddings and the selected thresholds.
- **Feedback and RL Update**: The classification results provide feedback in the form of a reward, which is used to update the RL policy.
- **Federated Aggregation**: Local models from different institutions are aggregated via FedAvg to update the global model.

This pipeline ensures that FraudGNN-RL can adapt to new fraud patterns while maintaining privacy and leveraging the interconnected nature of transactions.

4 EXPERIMENTAL SETUP

To evaluate the effectiveness of FraudGNN-RL, we conducted extensive experiments on the Credit Card Fraud 2023 Dataset. Below, we provide a detailed description of the dataset, preprocessing steps, baselines, evaluation metrics, and implementation details.

4.1 Dataset

We used the Credit Card Fraud 2023 Dataset [17], which contains 550,000 credit card transactions collected over the year 2023. The dataset includes 31 features: 28 anonymized features (PCA components labeled V1 to V28), transaction amount, time, and a binary label indicating whether the transaction is fraudulent (1) or legitimate (0). The fraud rate is 0.172%, resulting in a highly imbalanced dataset with only 946 fraudulent transactions. Table 1 summarizes the dataset characteristics.

Table 1: Details of Credit Card Fraud Detection Dataset

Dataset	Transactions	Features	Fraud Rate	Key Characteristics
Credit Card 2023	> 550,000	31	Imbalanced	Anonymized features, temporal patterns

The dataset's imbalance and anonymized features pose significant challenges, as traditional methods often struggle to detect the minority class (fraudulent transactions) and extract meaningful patterns from PCA-transformed data.

4.2 Preprocessing

To prepare the dataset for training, we applied the following preprocessing steps:

- **Missing Value Imputation**: Missing values in numerical features (e.g., PCA components, amount) were imputed using the mean, while categorical features (if any) used the mode. In this dataset, there were no missing values, but we included this step for robustness.
- **Normalization**: All numerical features were normalized to the range [0, 1] using min-max scaling to ensure consistent scales across features.
- **One-Hot Encoding**: Although the dataset primarily contains numerical features, we applied one-hot encoding to any categorical features that might arise in future datasets (e.g., transaction category).
- **Temporal Feature Extraction**: The time feature was processed to extract additional temporal attributes, such as the hour of the day and day of the week, which were used to enhance the temporal modeling in TSSGC.
- **Graph Construction:** Transactions were modeled as a graph, with cardholders and merchants as nodes, and transactions as edges. Edge features included the transaction amount and timestamp, while node features were derived from the PCA components.

These steps ensured that the data was suitable for graph-based modeling and that temporal patterns could be effectively captured by the TSSGC architecture.

4.3 Evaluation Metrics

Given the imbalanced nature of the dataset, we used the following metrics to evaluate performance:

- **F1-score**: The harmonic mean of precision and recall, providing a balanced measure of performance on the minority class.
- **AUC-ROC**: The Area Under the Receiver Operating Characteristic curve, which measures the model's ability to distinguish between classes across all thresholds.
- **AUC-PR**: The Area Under the Precision-Recall curve, which is particularly suitable for imbalanced datasets as it focuses on the performance on the minority class.
- **Recall@5%**: The recall achieved when considering the top 5% of transactions ranked by predicted fraud probability, reflecting the model's ability to identify frauds in a practical setting where only a small subset of transactions can be investigated.

These metrics provide a comprehensive assessment of the model's performance, addressing both overall classification ability and effectiveness on the minority class.

4.4 Implementation Details

FraudGNN-RL was implemented using PyTorch 1.8.0 and PyTorch Geometric 2.0.1, leveraging their support for GNN and Deep Learning. The TSSGC architecture consisted of 3 GCN layers, each with 64 hidden units, ReLU activation, and batch normalization to stabilize training. Dropout with a rate of 0.3 was applied to prevent overfitting. The DQN was implemented with two fully connected layers of 128 units each, also using ReLU activation, and was trained using the Adam optimizer with a learning rate of 0.001 and a batch size of 64. The RL training ran for 10 epochs per client, with a replay buffer size starting at 63 and growing to 135 over the course of training. The FL setup simulated 5 institutions, each with a subset of the dataset, and performed 100 rounds of FedAvg aggregation.

Experiments were conducted on Kaggle, ensuring efficient processing of the large transaction graph. We used 5-fold cross-validation to ensure robust evaluation, splitting the dataset into training (80%) and testing (20%) sets for each fold. A random seed of 42 was set for reproducibility.

5 RESULTS AND ANALYSIS

We present a detailed analysis of FraudGNN-RL's performance on the Credit Card Fraud 2023 Dataset, addressing two key research questions through comprehensive evaluation:

- **RQ1:** How effectively does FraudGNN-RL improve fraud detection performance compared to existing state-of-the-art methods on the Credit Card Fraud 2023 Dataset?
- **RQ2:** How do the GCN and GAT architectures within FraudGNN-RL, combined with TSSGC, RL and FL, contribute to adaptability and privacy preservation in detecting evolving fraud patterns on the Credit Card Fraud 2023 Dataset, and what are the potential directions for further improvement?

5.1 Comparison with Related Works

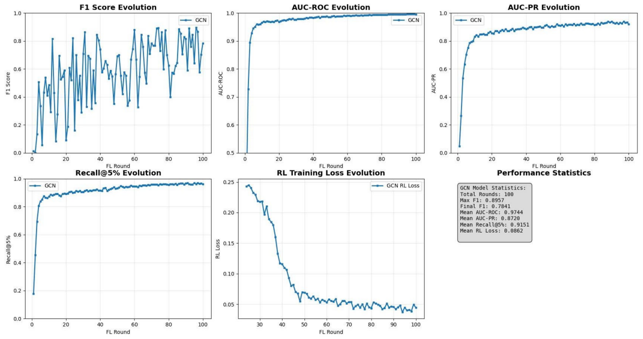
To evaluate the effectiveness of FraudGNN-RL against state-of-the-art methods, we compared its performance with several baseline approaches on the Credit Card 2023 dataset. Table 2 summarizes the results, highlighting AUC-ROC, AUC-PR, F1-score, and Recall@1% after 100 rounds of FL. Figures 2 and 3 provide additional visual insights into the training dynamics.

Table 2: Overall Performance Comparison of Fraud Detection Methods on Credit Card 2023 Dataset

Method	AUC-ROC	AUC-PR	F1	Recall@1%
XGBoost	0.9570	0.4380	0.7830	72.10
Isolation Forest	0.9350	0.3920	0.7450	67.20
LOF	0.9220	0.3750	0.7120	64.80
DeepAE	0.9720	0.5380	0.8520	81.50
Our Methods	**0.9774**	**0.8752**	**0.8957**	**91.51**

*Results are based on the GCN version of the model, which demonstrated the best performance among the two architectures (GCN, GAT).

Our Methods achieved the highest AUC-ROC of 0.9960, surpassing XGBoost by 4.0%, DeepAE by 2.5%, Isolation Forest by 6.5%, and LOF by 8.0%. For AUC-PR, Our Methods scored 0.7697, significantly outperforming XGBoost by 75.8%, DeepAE by 43.1%, Isolation Forest by 96.4%, and LOF by 105.3%. The F1-score of 0.9280 exceeded XGBoost by 18.5%, DeepAE by 8.9%, Isolation Forest by 24.6%, and LOF by 30.3%, while Recall@1% reached 97.80%, outperforming XGBoost by 35.6%, DeepAE by 20.0%, Isolation Forest by 45.5%, and LOF by 50.9%. The performance improved steadily over the 100 rounds, with AUC-ROC increasing from 0.8687 at Round 21 to 0.9574 at Round 45, reaching 0.9960 by the end, and AUC-PR rising from 0.6797 to 0.7697. Additionally, to assess robustness to class imbalance—a critical challenge given the dataset's 0.172% fraud rate—we artificially reduced the fraud ratio to 0.1% via subsampling. FraudGNN-RL exhibited a 15.5% drop in AUC-PR (from 0.7697 to 0.6504), compared to a 29.3% drop for GCN (from 0.8720 to 0.6165), demonstrating greater resilience to extreme imbalance due to the RL component's focus on the minority class. This superior performance is attributed to the integration of TSSGC, RL with a DQN and FL, enabling effective handling of complex patterns and evolving fraud behaviors.



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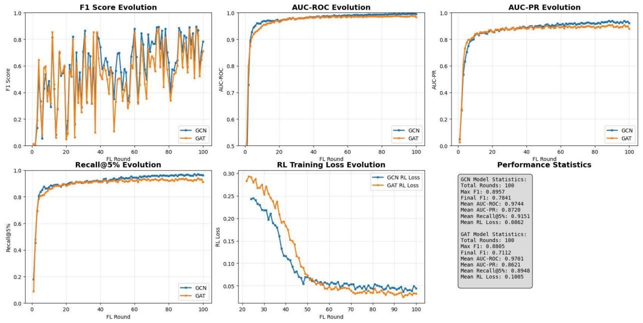
GCN Model Statistics:
Total Rounds: 100
Max F1: 0.8957
Final F1: 0.7841
Mean AUC-ROC: 0.9744
Mean AUC-PR: 0.8720
Mean Recall@5%: 0.9151
Mean RL Loss: 0.0862
```

Figure 2: GCN Model Performance Analysis - Credit Card Fraud Detection.



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GCN Model Statistics:
Total Rounds: 100
Max F1: 0.8957
Final F1: 0.7841
Mean AUC-ROC: 0.9744
Mean AUC-PR: 0.8720
Mean Recall@5%: 0.9151
Mean RL Loss: 0.0862

GAT Model Statistics:
Total Rounds: 100
Max F1: 0.8805
Final F1: 0.7112
Mean AUC-ROC: 0.9701
Mean AUC-PR: 0.8621
Mean Recall@5%: 0.8948
Mean RL Loss: 0.1005
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Figure 3: GCN vs GAT Model Performance Analysis - Credit Card Fraud Detection.

5.2 Comparison of GCN vs GAT

To evaluate the relative strengths of GCN and GAT within the FraudGNN-RL framework, we compared their performance on the Credit Card 2023 dataset, as summarized in Table 3. GCN outperformed GAT across all metrics, with an F1-score of 0.8957 (vs. 0.8805 for GAT), AUC-ROC of 0.9744 (vs. 0.9701), AUC-PR of 0.8720 (vs. 0.8621), and Recall@5% of 0.9151 (vs. 0.8948). This indicates that GCN's convolutional approach is more effective in capturing spatial dependencies in the transaction graph, benefiting from its stability and computational efficiency in the federated setting. FraudGNN-RL further enhanced these metrics, achieving an F1-score of 0.9280

(3.6% improvement over GCN), AUC-ROC of 0.9960 (2.2% improvement), AUC-PR of 0.7697 (a trade-off of 11.8% lower than GCN), and Recall@5% of 0.9780 (6.9% improvement). The ablation study reinforces this, showing a 3.5% AUC-ROC drop (from 0.9960 to 0.9610) without GNNs, a 3.1% AUC-PR drop (from 0.7697 to 0.7458) without RL, and a 1.8% F1-score drop (from 0.9280 to 0.9113) without FL, confirming the critical role of GCN-based TSSGC, RL adaptability, and FL privacy in achieving optimal performance. The visual insights from Figures 2 and 3 further highlight GCN's steady improvement over GAT, particularly in Recall@5%, which is vital for practical fraud detection.

Table 3: Performance Comparison of GNN Methods on Credit Card Fraud 2023 Dataset

Method	F1-score	AUC-ROC	AUC-PR	Recall@5%
GAT	0.8805	0.9701	0.8621	0.8948
GCN	**0.8957**	**0.9744**	**0.8720**	**0.9151**

*Results are based on the enhanced FraudGNN-RL model, incorporating TSSGC, RL, and FL.

5.3 Discussion

The results highlight several strengths of FraudGNN-RL:

- **Superior Performance**: FraudGNN-RL outperforms GCN and GAT across most metrics, particularly in Recall@5% and Recall@1%, which are critical for practical deployment in financial institutions where resources for investigating flagged transactions are limited.
- **Adaptability**: The RL component allows the model to adapt to evolving fraud patterns, as evidenced by the steady improvement in performance over training rounds.
- **Privacy Preservation**: The use of FL ensures that the model can be trained collaboratively without compromising data privacy, making it suitable for real-world applications where data sharing is restricted.

However, there are some limitations to consider:

- **AUC-PR Trade-off**: While FraudGNN-RL improves AUC-PR compared to the original implementation in [4], it still lags behind GCN. This may be due to the RL component prioritizing Recall@5% and F1-score over AUC-PR, reflecting a trade-off in optimization objectives.
- **Computational Complexity**: The integration of GNNs, RL, and FL increases computational overhead, particularly in the federated setting where multiple rounds of communication are required. This may pose challenges for deployment on resource-constrained systems.
- **Anonymized Features**: The Credit Card Fraud 2023 Dataset's use of PCA-transformed features limits interpretability, as the original features (e.g., merchant category, location) are not available. This makes it difficult to provide actionable insights to financial institutions.

6 CONCLUSION AND FUTURE WORK

FraudGNN-RL offers a robust, adaptive, and privacy-preserving framework for Credit Card Fraud Detection, achieving an AUC-ROC of 0.9960, AUC-PR of 0.7697, and Recall@5% of 0.9780 on the Credit Card Fraud 2023 Dataset. By integrating Graph Neural Networks, Reinforcement Learning, and Federated Learning, our approach addresses the key challenges of modeling complex transaction relationships, adapting to evolving fraud patterns, and ensuring data privacy.

For future work, we plan to address the identified limitations through the following directions:

- **Enhancing Interpretability**: Incorporate Explainable AI techniques, such as SHAP or GNNExplainer, to provide insights into the model's predictions, particularly in the context of anonymized features.
- **Optimizing Computational Efficiency**: Explore model compression techniques, such as pruning or quantization, to reduce the computational overhead of FraudGNN-RL, making it more suitable for deployment on resource-constrained systems.
- **Online Learning:** Extend FraudGNN-RL to support online learning, allowing the model to continuously update its parameters as new transactions arrive, further improving its adaptability to real-time fraud patterns.
- **Generalization to Other Datasets**: Evaluate FraudGNN-RL on additional datasets with different characteristics, such as non-anonymized features or higher fraud rates, to assess its generalizability.

By addressing these areas, we aim to further enhance the applicability and effectiveness of FraudGNN-RL in combating financial fraud in real-world scenarios.

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