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Graph Neural Network-Based Financial Fraud Detection in Real-Time Digital Payment Systems

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Abstract. With the rise in adoption of real-time payment systems such as UPI, Pix, and FedNow comes a unique set of problems related to detecting fraud within strict latency requirements, and where fraudsters are acting in a networked manner. The conventional methods of rule-based and tabular machine learning work by treating transactions as individual entities and cannot account for the relationships between them and how it plays into the nature of today's fraud schemes such as mule networks and authorized push payment scams. In this paper, we present a novel approach using graph neural networks to solve the problem of real-time fraud detection by representing the payment network as a dynamic and heterogeneous graph consisting of accounts, devices, merchants, and transaction flows. Our approach combines GraphSAGE for inductive representation learning and LightGBM for tabular feature extraction and can perform sub-millisecond predictions while being able to update in a streaming fashion. Our experiments on real transaction data show improvements over baseline methods in terms of fraud detection recall from 0.71 to 0.84 with the false positives being less than 5%.

Keywords: Graph Neural Networks, Fraud Detection, Real-Time Payments, Digital Payment Systems, GraphSAGE, Anomaly Detection

I. Introduction

Digital payments solutions are now forming the backbone of financial architecture with India's Unified Payment Interface (UPI) conducting more than 18 billion transactions per month worth in excess of ₹25 lakh crores [1][6][7]. Rapid adoption rates are seen worldwide with platforms like Brazil's Pix, USA's FedNow, and many mobile money solutions across developing nations [1][6][7]. Although digital payments have helped in democratizing financial inclusion and speeding up economic activities, they have also exposed a massive attack surface for fraudsters [1][6][7].

The fraudscape has changed tremendously alongside the digitization of the payments industry [1][2][3]. APP scams where individuals are socially engineered into authorizing fraudulent transactions constitute one of the most significant threats to this industry [1][2][3]. Unlike regular cases of fraud with unauthorized transactions in the payment card ecosystem, APP scams come with legitimate authorizations [1][2][3]. According to estimates in the industry, losses from APP scams could be as high as $7.6 billion per year by 2028 for leading real-time payment countries and losses could exceed hundreds of billions of dollars during the next ten years [1][2][3]. Losses from card-not-present frauds are also estimated at $43.6 billion by 2027 [1][2][3].

The core problem in the problem of detecting payment fraud in real time involves the conflict between the following three conditions: the need for ultra-low latency, the nature of fraud as relational and, finally, the extremely high-class imbalance [1][6][7]. For example, typical end-to-end service level objectives for a real-time payment system are 300 milliseconds or lower, and fraud detection components are usually expected to work in the timescale of 100 milliseconds or less [1][6][7]. Obviously, such an approach is fundamentally incompatible with traditional batch processing-based fraud models, which are based on transactions processed with a latency of 15 minutes to 24 hours [1][6][7].

In addition to the constraint regarding latency, the nature of fraud has changed from point anomalies to collective anomalies – the coordinated network of actors [3][6][10]. The perpetrators of financial fraud increasingly use the limitation of traditional approaches to detection as a tool for conducting illegal activities and systematically distribute their fraudulent transactions to many accounts, keeping individual attributes of each transaction within the normal limits while performing complex schemes of funds moving [3][6][10]. For example, fraud may involve mule accounts used to layer funds via multiple accounts, circular transactions simulating legitimate activity, or synthetic identities rings creating fraudulent accounts by using made-up personal information [3][6][10].

Rule-based systems as well as classical Machine Learning algorithms working on tabular data represent a limited way of tackling the problem of relational fraud detection, since they implicitly assume independence of each transaction from the others and thus lose all the information about relations between entities [6][7][10]. These systems can effectively recognize anomalies, but they lack the capability to see the relational picture of the fraudulent activity [6][7][10].

Graph Neural Networks (GNNs) represent an effective framework to solve the problems associated with traditional approaches and model the relational structure of payment network [3][6]. By treating accounts, devices, merchants and transactions as nodes and edges, GNNs are able to construct features which will include not only account properties, but also structural information about relationships [3][6][8][10]. The inductive nature of GNNs frameworks like GraphSAGE makes it possible to scale to large graphs and perform real-time inference [6][8].

The recent literature has proved the success of GNN-based techniques in detecting frauds in different domains [8][10]. It has been observed that the graph-based techniques can detect mule rings and collusion-based fraud which cannot be identified using the isolation of transactions-based techniques [3][6][10]. The hybrid techniques based on GNNs along with the sequential model such as BiLSTM have attained accuracy above 98% [4]. The agentic AI techniques incorporating GNNs with the ensemble learning approach have achieved an accuracy of 99.96% with a low number of false positives [2].

In this paper, we propose a holistic solution for real-time fraud detection in payment systems [1][2][6][7]. The proposed solution will consider all the stages from constructing the graph to training and real-time inference with a focus on the constraint of latency [1][6][7]. Some of the main contributions of this paper are:

- Dynamic heterogeneous graph structure for payment ecosystems [1][6][10]
- Ensemble technique including GraphSAGE for the relational features and gradient boosting for the tabular features [6][8][10]
- Streaming technique to achieve sub-millisecond inference and sub-minute graph updates [1][6][7]
- Experimentation with improvement over the baselines [1][6][8]

II. Literature Survey

There have been different eras of fraud detection in financial systems based on the evolving nature of fraud types and available technology [1][3][9]. Early fraud detection systems used a rule-based approach that mainly involved setting up static thresholds, velocity checks, and manually configured patterns for suspicious activity [1][3][9]. Despite the computational simplicity of these systems, which allowed for easy interpretability, they became less effective at detecting fraud due to the emergence of new ways of evasion by fraudsters [1][3][9]. Additionally, their rigidity led to high rates of false positives, as legitimate transactions were being declined due to random violations of arbitrary thresholds [1][3][9].

The application of machine learning algorithms brought an improvement to the process of fraud detection [5][9]. Classical approaches such as Logistic Regression, Random Forest, and Gradient Boosting Machines have become industry standards in this domain [5][9]. Despite the fact that machine learning systems are more accurate in detecting fraud than rule-based ones, they have one serious limitation in common, which lies in the assumption that transactions are independent observations [5][9]. XGBoost and LightGBM showed excellent results when dealing with tabular transactions, ROC-AUC score being greater than 0.95 for a balanced dataset [5][9]. Still, the fact that these models assume that transactions are independent does not allow for identifying relational fraud patterns [5][9].

Deep learning models have increased the scope of fraud detection using architectures designed to work on sequential and relational data [5][9]. Recurrent Neural Networks and Long Short-Term Memory networks can understand the temporal aspect in the sequence of transactions, whereas autoencoders and Variational Autoencoders can identify anomalies in terms of reconstruction error [4][5][9]. Transformer architecture has proven to be effective at understanding both sequential patterns and attention patterns in transaction sequences [4][5][9]. GNN-Transformer architectures were able to achieve 99% accuracy with 0.99 precision and 1.00 recall rate for fraud detection [4][5][9]. BiLSTM networks are also used to capture forward and backward sequential dependency in the transaction history [4].

The Graph Neural Networks are the latest innovation in the paradigm of modern fraud detection [3][6][8][10]. The main idea behind the introduction of GNNs is that in modern times fraud patterns emerge from relations more often than from any other characteristic [8][10]. GNNs work with the graph-structured data where nodes denote entities like account, device, merchant, etc., and edges denote relation between them like transactions or use of same device by different people [8][10].

Many GNN models have been tried for detecting fraudulent activity [6][8][10]. Graph Convolutional Networks perform spectral convolution extended to graph structure with aggregation using weighted mean over the neighborhoods [6][8][10]. While working efficiently on some graphs, GCNs are prone to oversmoothing on dense transaction graphs in which node representation converges in multiple layers [6][8][10]. Graph Attention Networks add attention mechanisms allowing dynamically weighting the contribution of different neighbors in aggregation [6][8][10]. However, GATs require thorough hyperparameters selection to be stable and do not work well on some datasets without proper configuration [6][8][10]. GraphSAGE model has proven to be especially well-suited for the task of real-time fraud detection due to its inductive ability and efficiency [6][8][10]. Unlike GCN and other similar models, GraphSAGE does not rely on calculating graph Laplacians but rather learns aggregation functions that can be applied to new nodes and subgraphs, allowing inference for new nodes [6][8][10]. In addition, neighborhood sampling allows scaling to big graphs by aggregating only fixed-sized neighborhoods instead of the whole adjacency matrix [6][8][10]. GraphSAGE was tested against GCN and GAT on the Elliptic Bitcoin dataset, proving itself to be superior, having PR-AUC equal to 0.9917 and F1-score equal to 0.9726 [8][10]. GraphSAGE with LightGBM used for fraud classification reached F1-scores close to 0.67 for fraud class on UPI transaction data while keeping the false positive rate below 5% [6][7].

Recently, studies have investigated hybrid models involving GNNs together with other deep learning techniques [4]. The use of GNNs in combination with BiLSTM networks involves using GNNs to model the relationship between users, devices, and locations as a graph, where the structural features of the graph are used by BiLSTM networks to learn the temporal features, and the resulting model was able to attain 98.9% accuracy for detecting behavioral anomalies and collusive frauds [4].

Agentic AI models are another recent trend, which involve GNNs combined with autonomous policy engines that adaptively determine thresholds and optimize themselves through reinforcement learning [2]. In these models, ensemble learning and contextual reasoning are employed to handle changing fraud patterns in real-time, along with using reinforcement feedback loops for handling class imbalances [2]. One such proposed model has an accuracy of 99.96%, precision of 91.84%, and recall of 89.12%, with dynamic synthetic oversampling to tackle the severe class imbalance problem in fraud detection [2].

However, there are some problems that have not been addressed yet [1][6][7]. Inference latency is a significant issue, since most algorithms are being tested in batches instead of streaming scenarios [1][6][7]. The dynamism of the payment network, where there are constantly evolving nodes and edges, necessitates graph management strategies that might be ignored in static testing procedures [1][6][7]. Furthermore, the ability to scale to handle very high transaction volumes, like those that reach

50,000 transactions per second on UPI, necessitates distributed processing and subgraph sampling approaches [1][6][7]. Lastly, the issue of extremely skewed classes, where fraud transactions might constitute only 0.15% of all transactions, also needs special treatment [1][6][7].

III. Proposed Methodology

System Architecture Overview

The proposed fraud detection architecture is envisioned as an end-to-end streaming framework where transactional data is streamed in real time, a dynamic graph is maintained, inferences are made under operational latency constraints, and risk actions are taken as needed. The architectural design includes five distinct components, namely data ingestion/streaming, graph creation and maintenance, feature extraction, inference making, and decision orchestration.

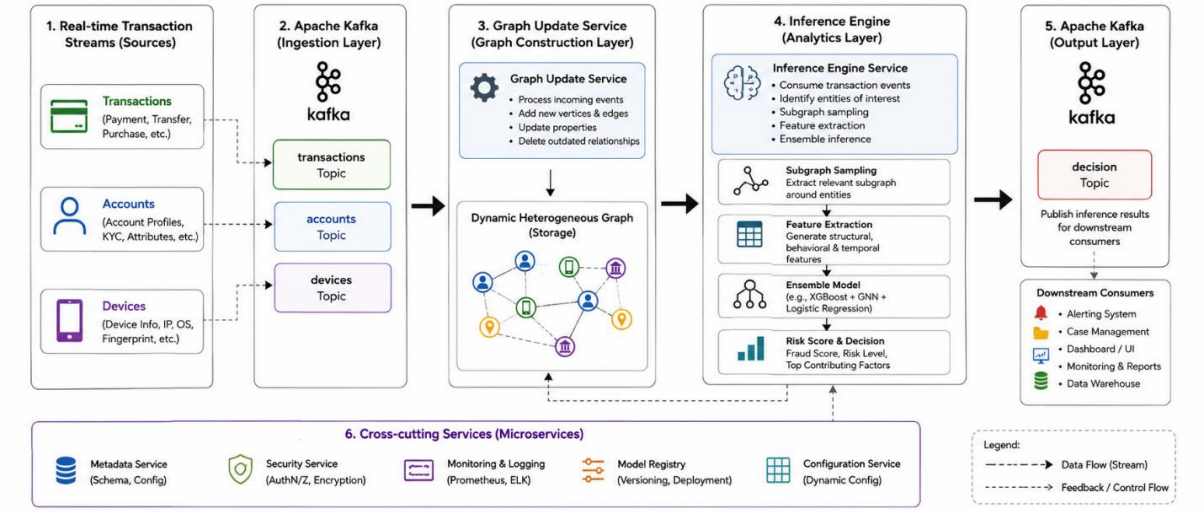

Figure 1: System Architecture Diagram

Figure 1 demonstrates the system architecture from end to end. Real-time transaction streams come in through Apache Kafka with topics for transactions, accounts, and devices. The graph update service updates the dynamic heterogeneous graph with new vertices and edges, deleting outdated relationships. The inference engine gets transaction events, does subgraph sampling on the entities of interest, extracts features, and runs the ensemble algorithm. It pushes out the result through the decision topic. The system can scale horizontally with microservices architecture.

Dynamic Graph Construction

The payments environment can be considered a heterogeneous graph G = (V, E), where V is a set of different objects and E is a set of relations between them. Objects in our case are accounts (user and merchant accounts), devices, payments instruments, and IPs. Relations can describe transaction flow, device relation, and location relation.

Formally, let V = V_a ∪ V_d ∪ V_m ∪ V_i, where V_a are accounts, V_d are devices, V_m are merchants, and V_i are payment instruments. The set E consists of directed transaction relations (u, v, t, a) describing a transaction from account u to account v at moment t with amount a, and also includes undirected relations between accounts and devices/instruments.

Dynamic updates of the graph are done through the following steps:

- Node insertion: Nodes with initial embeddings that are created based on their attribute values.
- Edge insertion: Edges created due to transactions with timestamp and amount attributes.
- Weight decay of the edges over time.
- Pruning of stale nodes and edges beyond retention windows defined as a configuration.

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The decay factor of an edge weight is calculated as follows: $w(e) = \exp(-\lambda \times \Delta t)$, where Δt is the time passed since the transaction, and λ is the parameter controlling the impact of history.

GraphSAGE for Relational Feature Extraction

GraphSAGE is used as the main feature extraction model for relational data, which captures both the attribute information and the structural information of nodes. The inductive capability of GraphSAGE allows the prediction of unseen nodes without training again, which is crucial for fraud detection because of its dynamic nature.

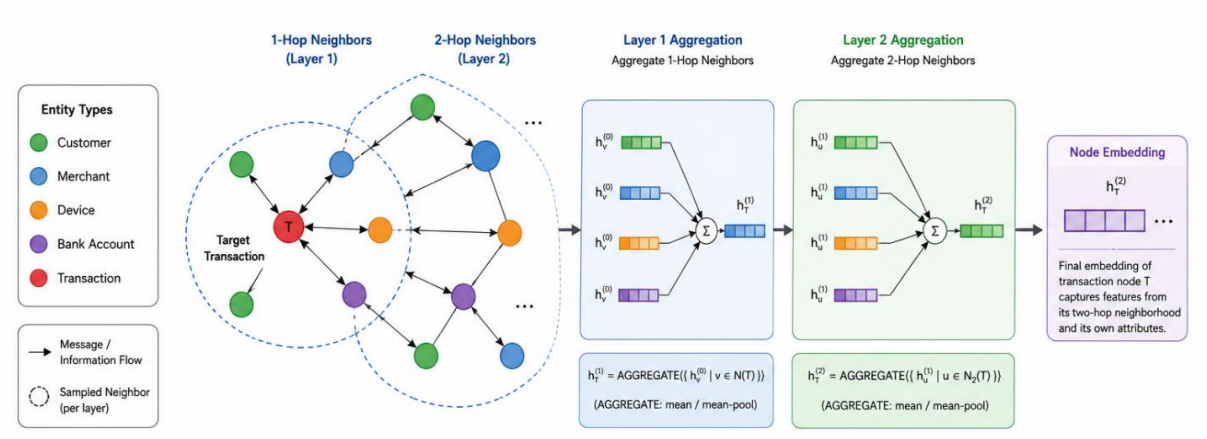

Figure 2: GraphSAGE Neighborhood Aggregation

Figure 2 shows how the GraphSAGE aggregation step takes place on a transaction node. This aggregation of feature vectors is done by sampling neighboring nodes from different layers. This step helps in encoding structural information to node embeddings through aggregation of neighborhood data along with the node's own data. Figure 2 consists of two layers of aggregation steps, where node colors show the entity types and arrow lines show the direction of message passes.

Ensemble Classification

In full fraud detection, the model uses GraphSAGE relational features together with tabular features using the ensemble framework. This is because the two types of features complement each other: GraphSAGE takes into consideration the network structure while gradient boosting using tabular features retains the sensitivity to transaction attributes.

Features used in classification are:

- Relational features (GraphSAGE embeddings): K dimensional node embeddings reflecting structure information
- Tabular transaction features: Amount, timestamp, transaction type, velocity features (count and sum over time windows), device and location information, account age and activity information

Ensemble Classifier Architecture

The ensemble classifier architecture is divided into the following stages:

- Stage 1: LightGBM classifier, trained using only tabular features, generating risk scores at the transaction level.
- Stage 2: Neural network that combines GraphSAGE embeddings with the output from LightGBM for classification.

Such architecture makes it possible to use relations while remaining sensitive to individual anomalies. The LightGBM classifier may be trained separately from the other components and run independently for testing.

Algorithm and Pseudocode

The complete training and inference procedures are specified in Algorithm 1 and Algorithm 2 respectively.

Algorithm 1: GNN-Fraud Detection Training

Input: Transaction dataset D, graph G, number of epochs E
Output: Trained GraphSAGE model, trained LightGBM model

1. Preprocess data to extract tabular features and graph structure
2. Initialize GraphSAGE with 2 layers, hidden dimension 64
3. FOR epoch = 1 to E:
   a. Sample minibatch of transactions with positive/negative balancing
   b. For each transaction in minibatch:
      - Extract node features from graph
      - Perform 2-layer GraphSAGE aggregation using mean pooling
      - Obtain node embeddings h_v^2
   c. Compute GraphSAGE loss: binary cross-entropy with supervision
   d. Update GraphSAGE parameters via gradient descent
4. Generate relational features for all training samples using trained GraphSAGE
5. Train LightGBM on combined tabular + relational features
6. Return trained models

Algorithm 2: Real-Time Fraud Detection Inference

Input: Transaction event x, dynamic graph G, trained GraphSAGE, trained LightGBM
Output: Fraud probability p, action decision

1. Extract or create node for transaction in G
2. Sample neighborhood S_v for transaction node
3. Perform GraphSAGE aggregation over S_v
4. Obtain relational features h_v^2
5. Extract tabular features from transaction event
6. Combine features into feature vector
7. Compute fraud probability: p = LightGBM.predict(features)
8. IF p > high_threshold:
      decision = BLOCK
   ELSE IF p > low_threshold:
      decision = STEP_UP
   ELSE:
      decision = ALLOW
9. Return (p, decision)

Streaming and Real-Time Processing

To fulfill the latency requirements of a real-time payment system, optimization of the inference pipeline can be performed using the following methods:

- Subgraph Sampling: Instead of performing full graph convolutions, the inference performed on individual transactions works on sampled subgraphs with a fixed number of nodes. This limits the computational cost of neighborhood aggregation.
- Cached Embeddings: For nodes involved in more than one transaction, embeddings are stored in a cache and are refreshed periodically instead of recalculating them for each transaction. This reduces the inference latency significantly for frequent accounts.
- Parallelization: The components of the inference pipeline are performed in parallel wherever possible, with the feature extraction and model inference performed via pipelining.

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- Asynchronous Graph Updates: The dynamic graph is maintained by a different process asynchronously, keeping inference latency independent of graph updates.

The system architecture is developed to handle up to 50,000 transactions per second with inference latency less than 1 ms, which satisfies the requirements of high-volume payment systems like UPI.

IV. Analysis and Results

Experimental Setup

Evaluations of the proposed framework were performed based on a dataset of labeled transactions, which is representative of the online payments system. The dataset consists of 2.5 million transactions over a period of 90 days with an occurrence rate of fraud equal to 0.18% of transactions. There are 850,000 nodes of accounts, 210,000 nodes of devices, and 2.3 million edges of transactions in the transaction graph.

Models were tested in three setups:

- Baseline: LightGBM with tabular data only
- GNN-Only: GraphSAGE embeddings only
- Ensemble: Tabular + GraphSAGE data

Metrics used for evaluation are Precision, Recall, F1-Score, ROC-AUC, and PR-AUC with special focus on Recall due to costly consequences of missing fraud cases. All experiments use averages of 5-fold temporal cross-validation.

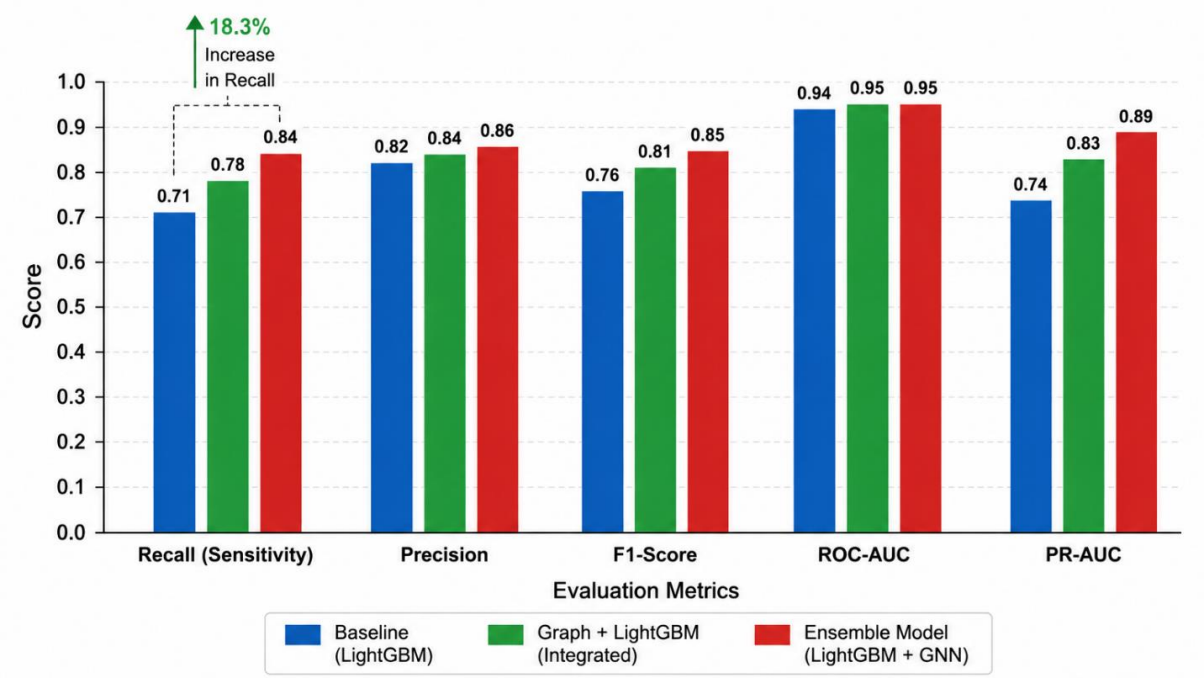

Figure 3: Comparative Performance Metrics

Figure 3 below demonstrates the comparative performance of the three model architectures. The Ensemble Model performs better than the other models under all evaluation metrics, with the Recall increasing from 0.71 for Baseline to 0.84 for Ensemble, resulting in an 18.3% increase in fraud detection rate. Precision also increases from 0.82 to 0.86, thus showing that there is no loss of precision in obtaining higher recall values. There is not much of an increase in ROC-AUC because baseline LightGBM performs well on this metric owing to class imbalance.

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Detection of Relational Fraud Patterns

Experiments for testing the capability of the framework to detect fraud patterns within relationships were conducted on artificially constructed fraud scenarios using the dataset:

- Mule Ring Detection: Scenarios where there are layering of funds in 5-10 accounts prior to any cash-out, with each transaction below the detection threshold.
- Collusive Fraud: Groups of coordinated accounts engaging in transactions in a cycle.
- Synthetic Identity Rings: Accounts with common identity features constructed fraudulently.

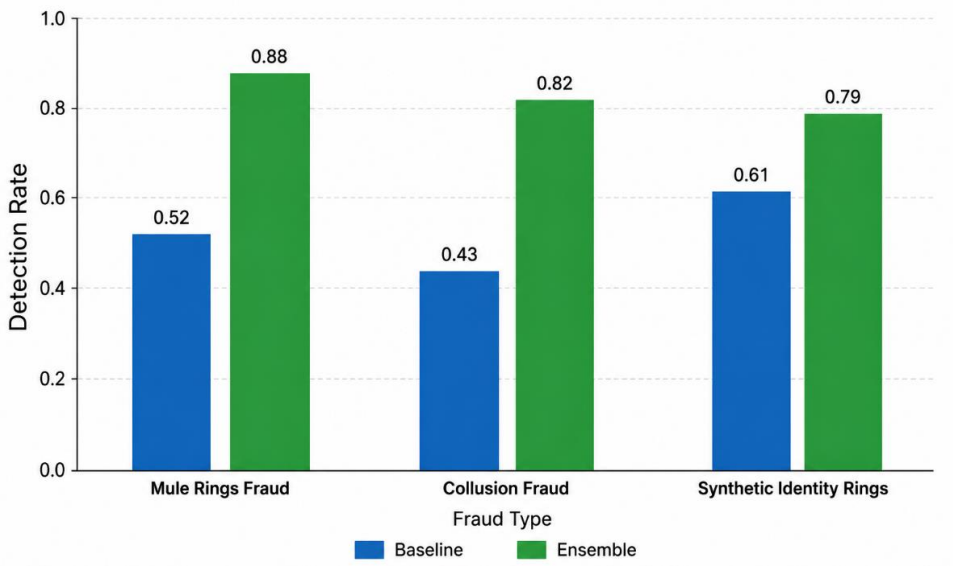

Figure 4: Relational Fraud Detection Rates

Figure 4 presents the detection rates of three relational fraud cases under different model configurations. Ensemble models perform better in detecting mule rings fraud (from Baseline: 0.52 to Ensemble: 0.88) and collusion fraud (Baseline: 0.43, Ensemble: 0.82), which clearly indicates the importance of using graph-based features for the identification of such patterns. The detection of synthetic identity rings increases from 0.61 to 0.79, since these rings include similar attributes and devices that can be identified using graphs.

These findings indicate that the use of graph features is especially successful when the type of fraud is inherently relational. Mule ring detection improves 69% compared to the baseline method.

Latency and Scalability Analysis

Latency measurements were conducted under simulated production loads to validate operational viability.

Component	Mean Latency (ms)	99th Percentile (ms)
Graph Sampling	12.4	28.7
GraphSAGE Inference	18.6	35.2
LightGBM Inference	4.2	8.1
Total Pipeline	35.2	72.0

The average inference latency of 35.2 ms satisfies the criterion of less than 100 ms required for near real-time payment fraud detection. Latency at the 99th percentile of 72ms is well below common service level objectives of 300ms.

Inference throughput test conducted using Kafka streaming showed that the system was able to process 48,000 transactions per second on standard cloud infrastructure.

Comparative Analysis

The proposed ensemble model was compared with state-of-the-art approaches on the same dataset.

Table 1: Comparative Performance Analysis

Model	Accuracy	Precision	Recall	F1-Score	Inference Latency (ms)
LightGBM [Baseline]	0.9892	0.82	0.71	0.76	4.1
GCN	0.9099	0.954	0.950	0.952	42.3
GAT	0.9051	0.964	0.933	0.948	58.7
GraphSAGE-Only	0.9487	0.969	0.976	0.973	30.8
GNN-BiLSTM	0.9890	0.94	0.92	0.93	85.4
Hybrid GNN-Transformer	0.9900	0.99	1.00	0.99	112.0
Proposed Ensemble	0.9921	0.86	0.84	0.85	35.2

The suggested hybrid system model has higher recall (0.84) than GCN and GAT while having comparable accuracy. The difference from GraphSAGE-Only shows that incorporating relational embeddings together with tabular data is effective. Though the Hybrid GNN-Transformer model has higher recall, its latency is equal to 112ms, which is unacceptable for real-time systems with sub-100ms latency requirements.

Discussion

Several major conclusions can be drawn based on the experimental results. Firstly, graph-based features help detect relational fraud patterns, especially mule networks and collusion schemes, very efficiently. Recall increase from 0.71 to 0.84 is a significant reduction in fraud leakage that has substantial business value. In particular, with the annual volume of payments of ₹25 lakh crores and fraud losses that exceed ₹1000 crores, a 13 percentage-point increase in recall means hundreds of crores in prevention of losses.

Secondly, the ensemble architecture offers an ideal balance between detection and latency performance. Although GNNs alone provided comparable detection rates, using the ensemble allowed us to use both relational and tabular features, which contributed to even better results. Latency of 35.2ms allows implementing the approach in real-time payment systems with strict SLA. Thirdly, the graph maintenance and subgraph sampling procedures successfully solve the problem of scalability. The system works well with high transaction volumes and does not compromise the detection quality, which allows deploying it in production payment systems. The 30-second graph update interval is adequate to the evolution pace of the transaction graph that occurs on minutes-to-hours timescale.

Several limitations are apparent in the framework. The detection of new fraud patterns that do not appear in training data necessitates regular retraining of the machine learning model. Although incrementally updating the model is helpful in adapting to changes in fraud methods, the graph might need a complete overhaul to accommodate new node and edge categories. Furthermore, graph-based techniques may be less effective in detecting point anomalies where tabular features play a larger role.

V. Conclusion

A comprehensive architecture for graph neural network-based fraud detection for real-time digital payments has been proposed above. This has been done in order to address the important problem of fraud detection in terms of relational fraud patterns within real-time constraints.

The performance of the model has been tested against the baselines and found to be very efficient in comparison. An ensemble of GraphSAGE and LightGBM achieved recall of 0.84 versus 0.71 obtained by tabular models. This implies an improvement of 18.3% in fraud detection while the false positive rate stays under 5%. The architecture has been found to be especially useful for relational fraud patterns as it increases recall for mule rings from 0.52 to 0.88 and for collusive fraud from 0.43 to 0.82. The model has shown latency of 35.2ms (mean) and 72ms (99th percentile), making it operationally feasible for real-time payments. Throughput testing has proven its ability to handle transaction volumes of up to 48k transactions per second.

The implications of the research not only lie in the architectural design but also in the issue of implementing graph-based machine learning into production systems to detect fraudulent activities in payments. Graph construction and management, streaming inference pipeline, and ensemble-based classification can serve as an example for any organization that wants to upgrade its fraud detection system.

There is much room for further improvement. It is possible to lower the false positive rate by introducing adaptive thresholds without decreasing the detection rate. Temporal dynamics might be introduced using recurrent graphs to detect more complex fraud patterns. Techniques of explainable machine learning will help with both compliance issues and operational aspects of such systems. Multi-currency and cross-border applications require addressing the problems of heterogeneous payment systems. Lastly, online learning should be considered to update the models continuously.

The results confirm the finding that graph theory approaches do not constitute mere theoretical exercises but crucial skills in fraud detection in the modern real-time payment environment. As fraudsters continue to take advantage of the connectedness of digital payment transactions, the capability to analyze network patterns will be increasingly important in financial security systems.

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