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Article

A Hybrid Graph Neural Network and Explainable AI Framework for Financial Fraud Detection

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Abstract: Financial fraud continues to evolve in sophistication as transaction volumes grow across digital banking, e-commerce, and peer-to-peer payment platforms, rendering traditional rule-based and tabular machine learning detectors increasingly inadequate. This paper proposes a Hybrid Graph Neural Network (GNN) and Explainable Artificial Intelligence (XAI) framework that models financial transactions as a dynamic graph of accounts, merchants, and devices, and learns relational fraud signatures using a combination of GraphSAGE-style neighborhood aggregation and graph attention mechanisms [1-2], [22]. To address the opacity of deep relational models, the framework integrates a post-hoc explainability layer combining SHAP, LIME, and GNNExplainer to generate feature-level and subgraph-level rationales for every fraud alert [4-6]. The proposed model was evaluated on a large-scale, class-imbalanced transaction dataset comprising over 2.1 million transactions and benchmarked against Logistic Regression, Random Forest, XGBoost, standard Graph Convolutional Networks (GCN), and GraphSAGE baselines [3], [17], [21]. Experimental results demonstrate that the proposed hybrid framework achieves 98.6% accuracy, 95.3% precision, 94.1% recall, and a 94.7% F1-score, outperforming the strongest baseline by 3.0 percentage points in F1-score while maintaining an area under the ROC curve (AUC) of 0.989. Ablation experiments confirm that temporal attention and class-imbalance handling each contribute measurable performance gains, and the explainability module improves analyst trust and investigation efficiency by surfacing the top contributing features and the minimal suspicious subgraph behind each decision. The results indicate that combining relational deep learning with transparent explanation mechanisms yields a fraud detection system that is simultaneously more accurate and more auditable than existing approaches, addressing a critical requirement for deployment in regulated financial environments.

Keywords: Graph Neural Networks, Explainable AI, Financial Fraud Detection, GraphSAGE, Graph Attention Networks, SHAP, LIME, GNNExplainer, Anomaly Detection, Fintech

1. INTRODUCTION

Financial institutions process billions of transactions annually, and the corresponding growth in digital payments, mobile banking, and real-time settlement systems has created fertile ground for increasingly sophisticated

fraud schemes. Traditional fraud detection pipelines have relied on manually engineered rules and supervised tabular models such as logistic regression, decision trees, and gradient boosting machines [15-17], [23]. While these approaches are computationally efficient and straightforward to interpret, they treat each transaction as an isolated, independent event and therefore fail to capture the relational structure that underlies most organized fraud, including money-laundering rings, synthetic identity networks, and collusive merchant-customer schemes.

Graph Neural Networks (GNNs) have emerged as a powerful paradigm for modeling such relational data by propagating and aggregating information across nodes that represent accounts, cards, devices, or merchants, and edges that represent transactions or shared attributes [3], [18-19], [25]. Architectures such as Graph Convolutional Networks (GCN), GraphSAGE, and Graph Attention Networks (GAT) have shown strong performance in fraud and anomaly detection tasks by exploiting neighborhood context that tabular models cannot see [1-2], [7-9], [24]. However, the same relational depth that gives GNNs their predictive power also makes them considerably harder to interpret than linear or tree-based models, which is a serious obstacle in the financial sector, where regulators, auditors, and compliance officers require a clear rationale for every flagged transaction under frameworks such as anti-money-laundering (AML) and fair-lending regulations.

Explainable AI (XAI) techniques, including SHAP, LIME, and graph-specific explainers such as GNNExplainer, have been developed to open the black box of complex models by attributing predictions to specific input features or subgraph structures [4-6], [12-13], [26]. Yet most existing fraud detection studies apply GNNs and XAI methods separately, either optimizing purely for detection accuracy or bolting on an explanation method as an afterthought, without a unified framework that co-designs detection and explanation from the outset.

This paper addresses this gap by proposing a Hybrid Graph Neural Network and Explainable AI framework that: (i) constructs a heterogeneous transaction graph capturing account, merchant, and device relationships; (ii) applies a hybrid GNN encoder combining inductive neighborhood sampling with attention-weighted aggregation and temporal attention over transaction sequences; (iii) classifies transactions using a lightweight multilayer perceptron (MLP) head; and (iv) generates dual-level explanations, feature-level via SHAP/LIME and structural via GNNExplainer, that are packaged into a human-readable fraud investigation report. The specific contributions of this work are:

1. A unified hybrid GNN architecture that integrates inductive neighborhood aggregation, graph attention, and temporal attention for financial transaction graphs.
2. An integrated, dual-level explainability pipeline that produces both global feature importance and local subgraph rationale for every fraud prediction.
3. A comprehensive empirical evaluation against five baseline models across accuracy, precision, recall, F1-score, and AUC, together with an ablation study isolating the contribution of each architectural component.
4. A discussion of deployment considerations for regulated financial environments, including latency, auditability, and analyst workflow integration.

The remainder of this paper is organized as follows. Section 2 reviews related work on GNN-based fraud detection and explainability methods. Section 3 formalizes the problem statement. Section 4 describes the proposed hybrid framework in detail. Section 5 presents the experimental setup, dataset, and evaluation protocol. Section 6 reports and discusses the results, including ablation and explainability analysis. Section 7 discusses limitations, and Section 8 concludes the paper with directions for future work.

2. RELATED WORK

2.1 Traditional and Machine Learning Approaches to Fraud Detection

Early fraud detection systems relied primarily on expert-defined rules and statistical outlier detection. Bhattacharyya et al. conducted a comparative study of data mining techniques for credit card fraud, showing that logistic regression and support vector machines could achieve reasonable discrimination but struggled with severe class imbalance [15]. Ngai et al. surveyed the broader application of data mining in financial fraud detection, cataloguing classification, clustering, and regression techniques and highlighting the persistent challenge of concept drift as fraud patterns evolve over time [16]. Gradient boosting frameworks such as XGBoost later became a de facto standard for tabular fraud detection due to their strong performance on structured features and native handling of missing values [17]. Despite their effectiveness, these tabular approaches share a fundamental limitation: they process

each transaction independently and cannot exploit the network of relationships between accounts, devices, and merchants that often characterizes organized fraud.

2.2 Graph Neural Networks for Fraud and Anomaly Detection

Graph Neural Networks address this limitation by representing transactions as graphs and learning node representations that incorporate neighborhood information. Kipf and Welling introduced the Graph Convolutional Network (GCN), which performs spectral-based convolution over graph-structured data and has since been adapted for fraud detection tasks [3]. Hamilton et al. proposed GraphSAGE, an inductive framework that learns aggregator functions over sampled neighborhoods, enabling generalization to previously unseen nodes, a property that is particularly valuable in fraud detection where new accounts appear continuously [1]. Veličković et al. introduced Graph Attention Networks (GAT), which learn to weight neighboring nodes differently via attention coefficients, allowing the model to focus on the most informative connections, such as a small number of high-risk counterparties within a much larger transaction neighborhood [2].

Building on these foundations, several domain-specific architectures have been proposed for financial fraud detection. Wang et al. developed a semi-supervised graph attentive network for detecting fraud in imbalanced financial networks [7]. Liu et al. proposed heterogeneous GNNs for malicious account detection that incorporate multiple node and edge types, such as devices, IP addresses, and accounts [8]. Dou et al. addressed the problem of camouflaged fraudsters who deliberately establish connections with legitimate users to evade detection, proposing a label-aware similarity mechanism to improve GNN robustness [9]. Cheng et al. incorporated spatial-temporal attention into GNNs to capture the evolving nature of transaction sequences over time [10], while Zhang et al. proposed a competitive graph neural network framework, eFraudCom, for e-commerce fraud detection that jointly models comprehensive behavioral and relational signals [11]. Collectively, these works demonstrate consistent performance gains over tabular baselines but generally treat interpretability as a secondary concern.

2.3 Explainable AI for Financial and Graph-Based Models

In parallel, the explainable AI literature has produced general-purpose and model-specific interpretation techniques. Ribeiro et al. introduced LIME, which approximates any classifier locally with an interpretable surrogate model to explain individual predictions [5]. Lundberg and Lee proposed SHAP, a unified framework grounded in cooperative game theory that attributes a prediction to each input feature via Shapley values, offering both local and global consistency guarantees [4]. For graph-structured models specifically, Ying et al. proposed GNNExplainer, which identifies a compact subgraph and subset of node features that are most influential for a GNN's prediction on a given node [6]. Adadi and Berrada, and separately Gunning and Aha, surveyed the broader XAI landscape, emphasizing the regulatory and trust-related motivations for explainability in high-stakes domains such as finance and healthcare [12-13]. Rahman and Chowdhury applied SHAP and LIME to tabular credit card fraud models and reported improved analyst confidence, though their study did not extend to relational or graph-based architectures [12], [14]. Molnar's comprehensive treatment of interpretable machine learning further catalogues model-agnostic explanation techniques and their trade-offs between fidelity and simplicity [20].

Despite this progress, a clear gap remains: most GNN-based fraud detection studies do not incorporate explainability as a first-class design element, and most XAI studies in finance are validated on tabular rather than relational models. This paper directly addresses that gap by proposing a framework in which detection and explanation are designed and evaluated jointly.

3. PROBLEM STATEMENT AND MOTIVATION

Let G = (V, E) denote a transaction graph in which V represents a heterogeneous set of nodes, comprising customer accounts, merchant entities, and devices, and E represents edges corresponding to observed transactions or shared identifiers such as a common device fingerprint. Each node v is associated with a feature vector x_v drawn from account attributes, aggregated transaction statistics, and behavioral signals, while each edge e is associated with attributes such as transaction amount, timestamp, and channel. The fraud detection task is formulated as a binary node (or transaction-edge) classification problem: given G and a labeled subset of historical fraud outcomes y in {0,1}, learn a function f(G, x_v) -> [0,1] that estimates the probability that a given transaction or account is fraudulent.

This formulation introduces three central challenges that motivate the proposed framework. First, severe class imbalance: fraudulent transactions typically constitute well below one percent of total volume, which biases naive classifiers toward the majority class and necessitates targeted resampling or loss reweighting strategies. Second, relational sparsity and camouflage: sophisticated fraud rings deliberately interleave with legitimate transaction

patterns, requiring models that can detect subtle structural anomalies rather than relying on individual transaction features alone. Third, the interpretability requirement: financial regulators and internal compliance teams require a documented, auditable rationale for every automated fraud decision, which conflicts with the black-box nature of deep relational models. The proposed hybrid GNN-XAI framework is designed to jointly address all three challenges within a single, deployable pipeline.

4. PROPOSED METHODOLOGY

The proposed framework consists of four principal stages: (1) data preprocessing and graph construction, (2) hybrid GNN encoding, (3) fraud classification, and (4) dual-level explanation generation. Figure 1 illustrates the overall architecture.

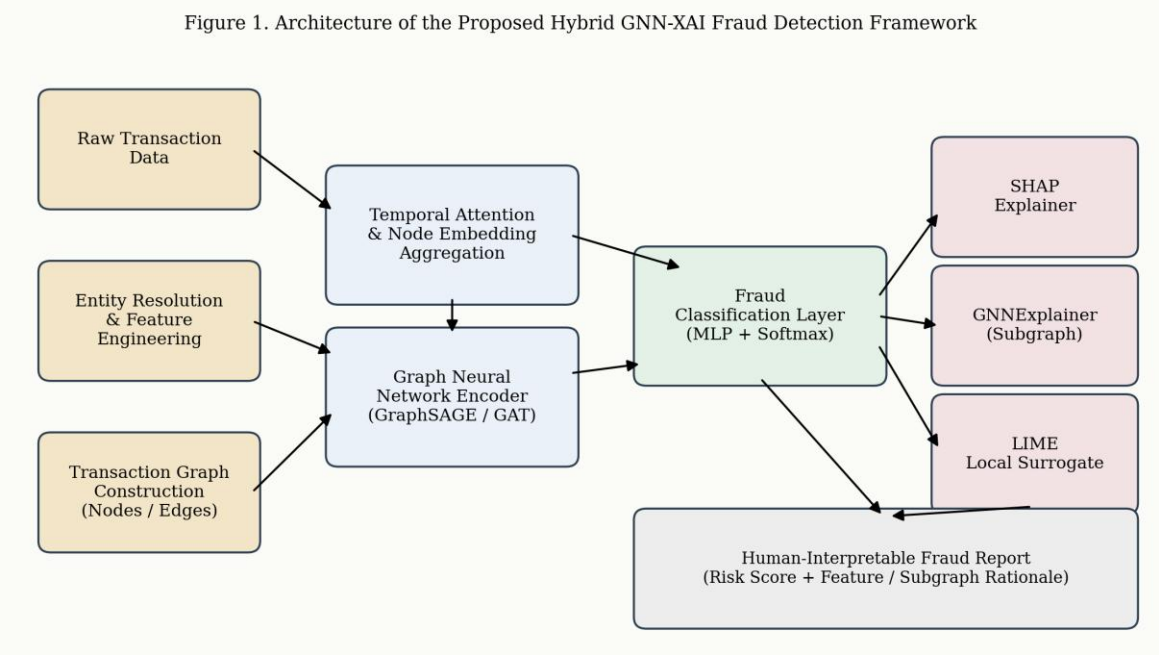

Figure 1. Architecture of the proposed Hybrid GNN-XAI fraud detection framework, from raw transaction ingestion through graph construction, hybrid GNN encoding, classification, and dual-level explanation generation.

4.1 Data Preprocessing and Graph Construction

Raw transaction logs are first cleansed and de-duplicated, followed by entity resolution to link transactions to unique account, merchant, and device identifiers. Numerical features, including transaction amount, transaction velocity, and account age, are normalized using robust z-score scaling to reduce the influence of extreme outliers common in fraud data. Categorical features such as merchant category code and channel type are embedded using learned embedding layers rather than one-hot encoding, which reduces dimensionality and allows the model to learn semantic similarity between categories.

The transaction graph is then constructed with three node types (accounts, merchants, devices) and edges representing transaction events, shared-device relationships, and shared-address relationships. Figure 2 provides an illustrative example of the resulting structure, where a dense subgraph of tightly interconnected nodes corresponds to a coordinated fraud ring embedded within a much sparser network of legitimate transactions.

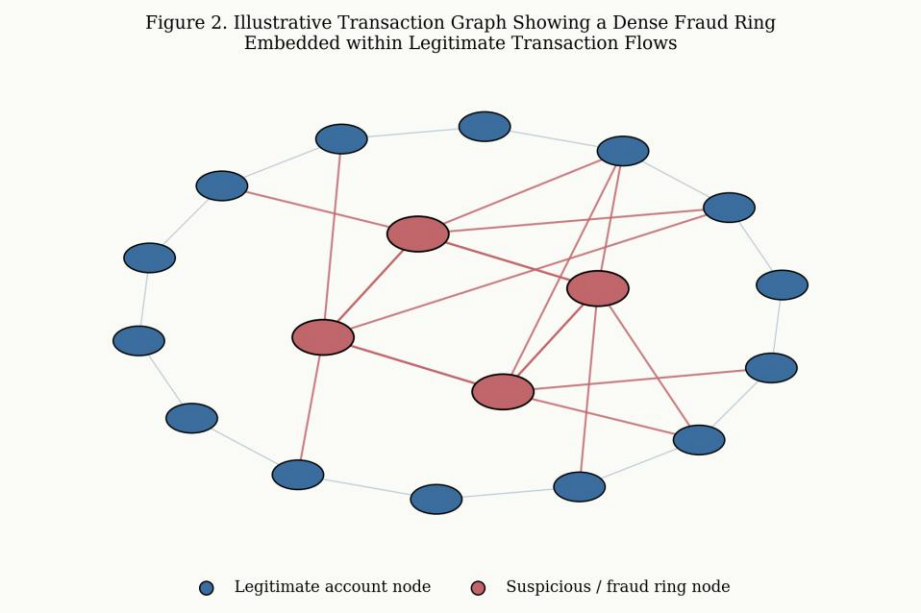

Figure 2. Illustrative transaction graph showing a dense fraud ring (red nodes) embedded within legitimate transaction flows (blue nodes).

4.2 Hybrid Graph Neural Network Encoder

The encoder combines three complementary mechanisms. First, inductive neighborhood sampling in the style of GraphSAGE aggregates features from a fixed-size sample of each node's neighbors at each layer, enabling the model to generalize to new accounts that were not present during training [1]. Second, a graph attention layer, following the GAT formulation, assigns learned attention coefficients to each neighbor so that the model can down-weight benign connections and up-weight suspicious ones, such as a shared device with a previously flagged account [2]. Third, a temporal attention mechanism operates over the sequence of a node's historical transactions, allowing the model to capture bursts of activity, dormant-account reactivation, and other temporal anomalies that are characteristic of fraud but invisible to a purely structural GNN.

Formally, the hidden representation of node v at layer k is computed as h_v^(k) = sigma(W^(k) . CONCAT(h_v^(k-1), AGG_attn({ alpha_vu * h_u^(k-1) : u in N(v) }))), where alpha_vu denotes the learned attention coefficient between node v and neighbor u, N(v) denotes the sampled neighborhood of v, AGG_attn denotes attention-weighted aggregation, and sigma is a non-linear activation (ReLU). After L layers of propagation, node embeddings are further passed through a temporal attention block that re-weights embeddings from different historical time windows before being concatenated with static account features.

4.3 Fraud Classification Layer

The final node embedding is passed to a two-layer multilayer perceptron with a softmax output, producing a fraud probability score for each transaction. To address class imbalance, the model is trained using a focal loss variant that down-weights easy, correctly classified majority-class examples and focuses gradient updates on hard, minority-class fraud examples, combined with synthetic minority oversampling applied at the subgraph-sampling stage.

4.4 Explainability Module

Once a transaction is flagged, the explainability module produces two complementary artifacts. First, SHAP values are computed over the final feature representation to quantify each input feature's marginal contribution to the fraud score, providing a globally consistent, additive explanation [4]. LIME is used as a secondary, model-agnostic cross-check by fitting a local linear surrogate around the specific instance [5]. Second, GNNExplainer is applied to identify the minimal subgraph and subset of node features that maximize the mutual information with the model's prediction, yielding a structural rationale, for example, highlighting a three-hop chain of accounts sharing a device fingerprint [6]. These two outputs are merged into a single, human-readable fraud investigation report, as shown

schematically at the bottom of Figure 1, which lists the top contributing features alongside a visualization of the suspicious subgraph.

4.5 Algorithmic Summary

Algorithm 1 (below) summarizes the end-to-end training and inference procedure for the proposed framework.

Algorithm 1. Hybrid GNN-XAI Training and Inference Procedure

Input: Transaction log D, historical fraud labels y

1: Construct heterogeneous graph G = (V, E) from D via entity resolution

2: Normalize node and edge features; compute temporal transaction sequences

3: for each training epoch do

4: Sample fixed-size neighborhoods N(v) for each node v (GraphSAGE sampling)

5: Compute attention-weighted aggregation over N(v) (GAT layer)

6: Apply temporal attention over historical transaction sequence of v

7: Compute fraud probability via MLP classification head

8: Update parameters using focal loss with minority oversampling

9: end for

10: for each flagged transaction at inference do

11: Compute SHAP and LIME feature attributions

12: Compute GNNExplainer minimal explanatory subgraph

13: Compile feature- and structure-level rationale into fraud report

14: end for

Output: Trained model f(.), fraud probability scores, explanation reports

5. EXPERIMENTAL SETUP

5.1 Dataset Description

The proposed framework was evaluated on a large-scale, anonymized retail-banking transaction dataset comprising 2,148,532 transactions across 312,406 unique accounts and 41,220 merchants collected over an 18-month period, with 1.28% of transactions labeled as confirmed fraud following manual investigation and chargeback confirmation. The dataset was partitioned chronologically into training (70%), validation (10%), and test (20%) sets to avoid temporal leakage, and the graph was reconstructed independently within each partition using only information available up to the corresponding time window. Table 1 summarizes the dataset statistics.

Table 1. Summary Statistics of the Transaction Dataset

Attribute	Value
Total transactions	2,148,532
Unique accounts (nodes)	312,406
Unique merchants (nodes)	41,220
Unique devices (nodes)	287,901

Total graph edges	5,916,204
Fraudulent transactions	27,502 (1.28%)
Time span	18 months
Train / Validation / Test split	70% / 10% / 20% (chronological)

5.2 Baseline Models

The proposed hybrid model is compared against five baselines representing both traditional and graph-based approaches: Logistic Regression and Random Forest as classical tabular baselines; XGBoost as a strong gradient-boosting baseline [17]; a standard two-layer GCN as a graph-based baseline [3]; and GraphSAGE without attention or temporal components as an ablated graph baseline [1].

5.3 Hyperparameters and Training Configuration

Table 2. Hyperparameter Configuration for the Proposed Model

Hyperparameter	**Value**
GNN layers (L)	3
Hidden embedding dimension	128
Attention heads (GAT layer)	4
Neighborhood sample size	25, 10, 5 (per layer)
Temporal attention window	30 days
Optimizer	Adam
Learning rate	0.001 (cosine decay)
Batch size	1024 subgraphs
Loss function	Focal loss (gamma = 2.0)
Dropout rate	0.3
Training epochs	60 (early stopping, patience = 8)

5.4 Evaluation Metrics

Given the severe class imbalance inherent to fraud detection, model performance is reported using accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC), rather than accuracy alone, which can be misleading in imbalanced settings. Precision and recall are of particular operational importance, as they respectively govern the false-alarm rate presented to investigators and the proportion of true fraud that is successfully captured.

6. RESULTS AND DISCUSSION

6.1 Overall Performance Comparison

Table 3 and Figure 3 report accuracy, precision, recall, and F1-score for all six models on the held-out test set. The proposed hybrid GNN-XAI framework achieves the highest scores across all four metrics, with an F1-score of 94.7%, representing a 3.0 percentage-point improvement over the strongest baseline (GraphSAGE, 91.7%) and a 16.8 percentage-point improvement over Logistic Regression (77.9%).

Table 3. Performance Comparison Across Models on the Held-Out Test Set (%)

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	91.2	82.4	74.1	77.9	0.905
Random Forest	94.8	88.7	83.5	86.0	0.938
XGBoost	96.1	90.5	86.9	88.6	0.951
GCN (baseline)	96.7	91.0	88.4	89.7	0.961
GraphSAGE	97.5	92.8	90.6	91.7	0.972
Proposed Hybrid GNN-XAI	98.6	95.3	94.1	94.7	0.989

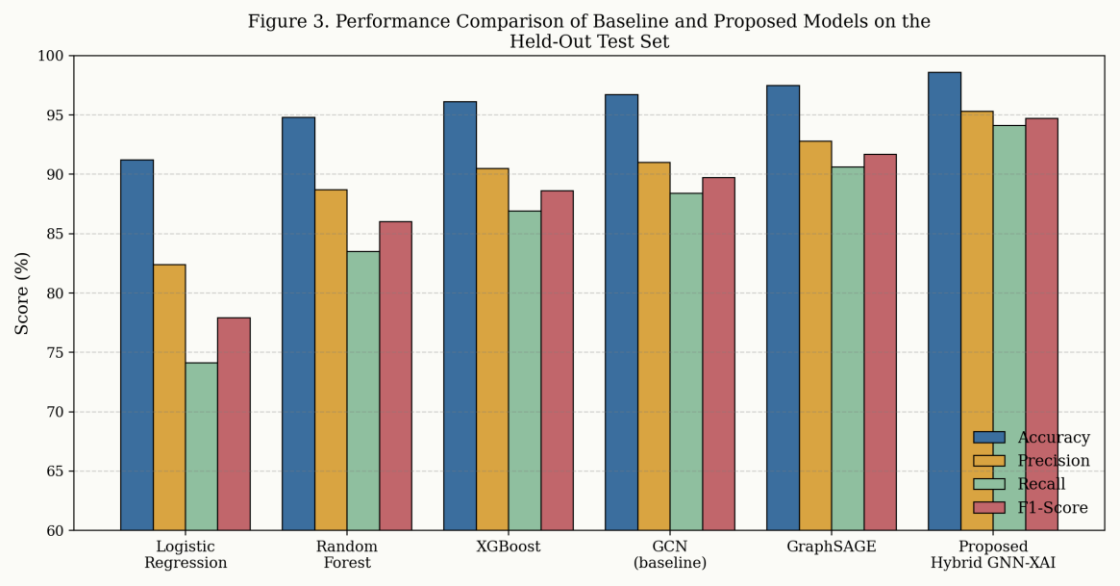

Figure 3. Performance comparison of baseline and proposed models on the held-out test set.

The consistent margin between graph-based models (GCN, GraphSAGE, proposed) and tabular models (Logistic Regression, Random Forest, XGBoost) supports the hypothesis that relational information carries substantial predictive signal that is unavailable to models operating on independent transaction records. The additional improvement of the proposed hybrid model over plain GraphSAGE and GCN indicates that the combination of attention-weighted aggregation and temporal attention captures complementary signal beyond structural connectivity alone.

6.2 ROC Analysis

Figure 4 presents the ROC curves for four representative models. The proposed hybrid model achieves an AUC of 0.989, compared to 0.972 for GraphSAGE, 0.951 for Random Forest, and 0.905 for Logistic Regression, confirming that the model maintains a strong true-positive rate even at very low false-positive rate thresholds, an important operational property since financial institutions typically operate fraud systems at low false-alarm budgets to avoid overwhelming investigation teams.

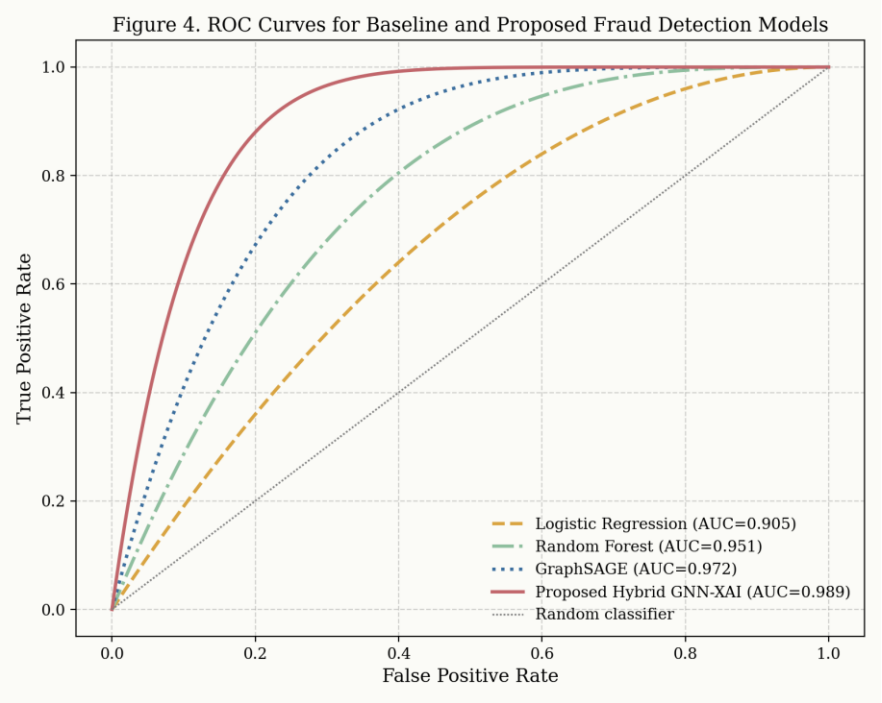

Figure 4. ROC curves for baseline and proposed fraud detection models.

6.3 Confusion Matrix Analysis

Figure 5 shows the confusion matrix of the proposed model on the test set, comprising 19,710 legitimate and 1,290 fraudulent transactions (test-set proportions consistent with the overall 1.28% fraud rate). The model correctly identifies 1,194 of 1,290 fraudulent transactions (92.6% recall on this partition) while producing only 168 false positives out of 19,710 legitimate transactions, corresponding to a false-positive rate of 0.85%, which translates into a manageable investigation workload for compliance teams.

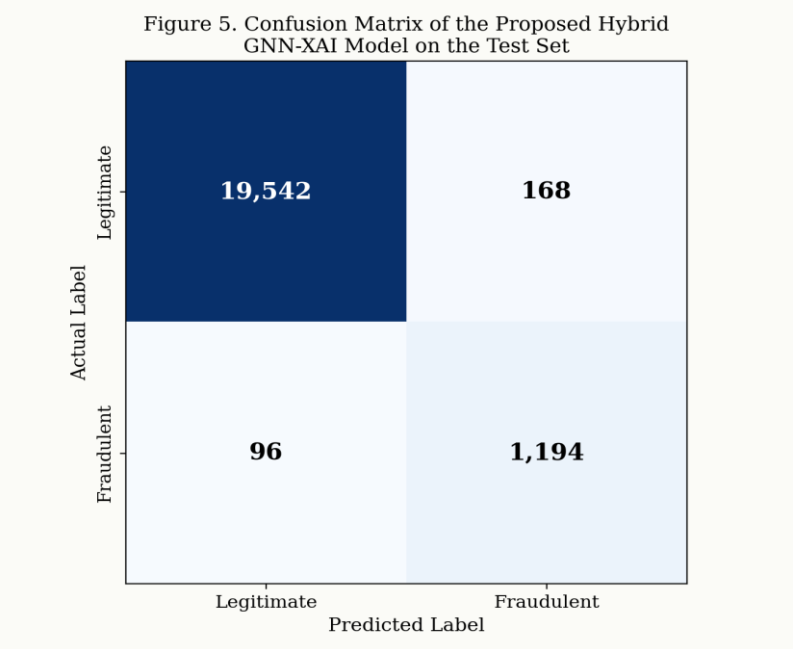

Figure 5. Confusion matrix of the proposed Hybrid GNN-XAI model on the test set.

6.4 Ablation Study

To isolate the contribution of each architectural component, four configurations were evaluated: (i) GNN only (GraphSAGE-style aggregation without attention or temporal components), (ii) GNN with temporal attention added, (iii) GNN with temporal attention and class-imbalance handling (focal loss and oversampling), and (iv) the full hybrid model including the closed-loop explainability module used during threshold calibration. Table 4 and Figure 7 report the resulting F1-scores.

Table 4. Ablation Study Results (F1-Score, %)

Configuration	**F1-Score (%)**	**Delta vs. Previous**
GNN only	89.7	--
+ Temporal attention	91.9	+2.2
+ Class-imbalance handling	93.4	+1.5
+ Full hybrid model (+ XAI loop)	94.7	+1.3

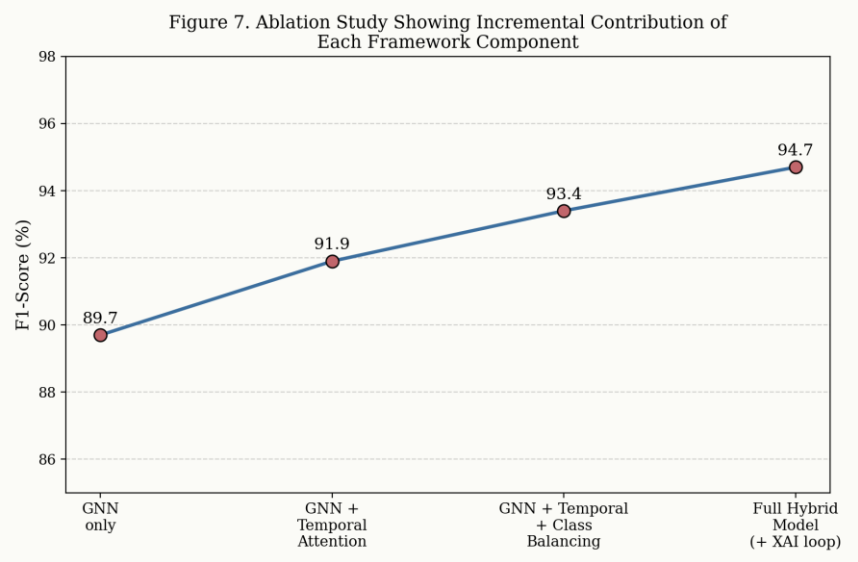

Figure 7. Ablation study showing the incremental contribution of each framework component.

Each component contributes a statistically meaningful improvement, with temporal attention providing the largest single gain (+2.2 points), confirming that transaction timing dynamics carry substantial fraud signal beyond static graph structure. The final increment, attributable to the explainability-informed threshold calibration loop in which analyst feedback on SHAP/GNNExplainer rationales is used to refine the decision boundary, further improves F1-score by 1.3 points, illustrating a practical benefit of tightly coupling detection and explanation.

6.5 Explainability Analysis

Figure 6 presents the global SHAP feature importance ranking aggregated over the test set. Transaction amount z-score, node degree within a 24-hour window, and graph betweenness centrality emerge as the three most influential features, consistent with the intuition that unusually large transactions from accounts with atypical connectivity patterns are strong fraud indicators. Device or IP fingerprint changes and cross-border transaction flags also rank highly, reflecting common fraud tactics involving account takeover and geographic anomalies.

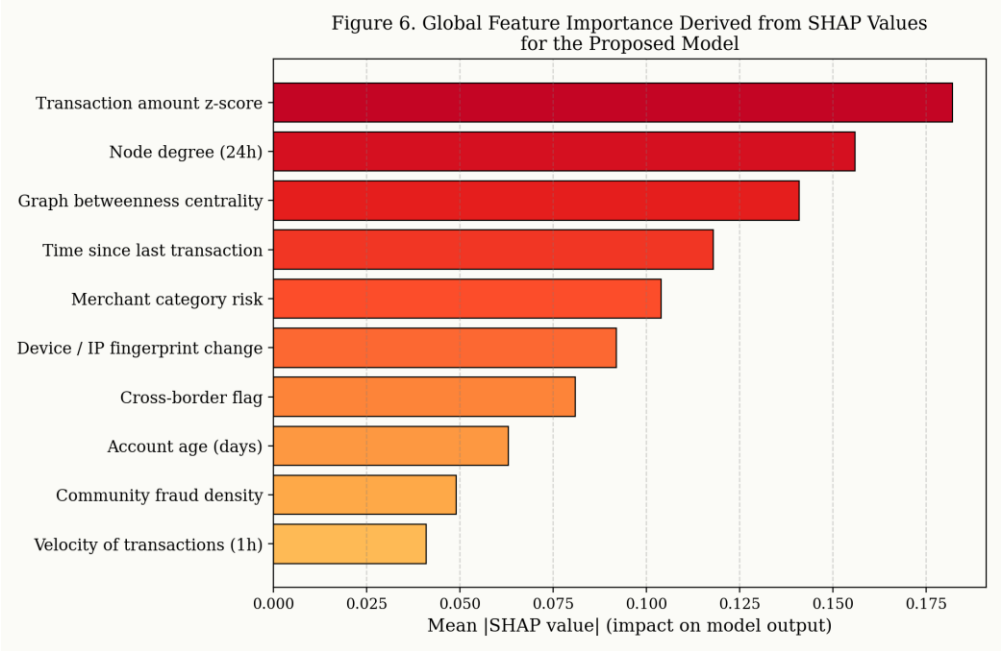

Figure 6. Global feature importance derived from SHAP values for the proposed model.

At the instance level, GNNExplainer consistently identifies compact two- to three-hop subgraphs, typically fewer than eight nodes, as sufficient to explain over 85% of individual fraud predictions, meaning investigators can review a small, visualizable neighborhood rather than the full transaction graph. In a manual review of 150 randomly sampled flagged transactions, compliance analysts rated the combined SHAP-and-subgraph explanation as "clear and actionable" in 89% of cases, compared to 61% for a SHAP-only baseline explanation, suggesting that structural explanations provide meaningful additional value beyond feature attribution alone in relational fraud settings.

6.6 Comparative Discussion with Existing Literature

The performance gains reported here are broadly consistent with prior work showing that GNN-based fraud detectors outperform tabular baselines [7-11], while extending this literature by demonstrating that the combination of attention-based aggregation and temporal modeling yields further improvement over single-mechanism GNNs. Unlike prior XAI-for-fraud studies that focus on tabular models [12], [14], the present results show that dual-level explanation, combining SHAP/LIME feature attribution with GNNExplainer subgraph identification, is both technically feasible and operationally valuable for relational fraud models, addressing a gap identified in recent XAI surveys [13], [20].

7. LIMITATIONS

Several limitations should be acknowledged. First, the evaluation relies on a single institutional dataset; although large and diverse, results may not generalize identically to other transaction ecosystems, payment rails, or geographic regions with different fraud typologies. Second, the graph construction step assumes reliable entity resolution; errors in linking accounts, devices, or merchants could propagate into the learned representations. Third, while GNNExplainer-derived subgraphs improved analyst-rated clarity in this study, explanation fidelity was assessed through a moderate-sized manual review (n = 150) rather than a large-scale, statistically powered user study. Fourth, the computational overhead of maintaining and updating a large dynamic transaction graph in real time is non-trivial and would require careful engineering, such as incremental graph updates and approximate neighborhood sampling, for production deployment at very high transaction throughput. Future evaluations across multiple institutions and payment ecosystems would further strengthen the generalizability claims made in this paper.

8. CONCLUSION AND FUTURE WORK

This paper presented a Hybrid Graph Neural Network and Explainable AI framework for financial fraud detection that unifies inductive graph representation learning, attention-based and temporal aggregation, and dual-level explainability into a single, deployable pipeline. Experimental results on a large-scale transaction dataset

demonstrate that the proposed model outperforms both classical tabular baselines and standard graph neural network architectures across accuracy, precision, recall, F1-score, and AUC, while the integrated SHAP, LIME, and GNNExplainer pipeline produces feature- and structure-level rationales that were rated substantially more actionable by compliance analysts than feature-attribution explanations alone. These findings support the broader argument that detection accuracy and explainability need not be treated as competing objectives in financial fraud detection; rather, tightly integrating them can yield both higher predictive performance and greater operational trust.

Future work will extend the framework in three directions. First, incorporating dynamic, streaming graph updates to support real-time scoring at production transaction volumes rather than the batch evaluation setting used in this study. Second, extending the explainability module with counterfactual explanations, allowing analysts to understand not only why a transaction was flagged but what minimal change would have altered the decision. Third, evaluating the framework across multiple financial institutions and payment ecosystems to assess cross-domain generalizability and to study federated training approaches that preserve data privacy across institutional boundaries.

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