International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 10, Issue 5, pp 40-46, May-2026

https://doi.org/10.47001/IRJIET/2026.105006

Explainable Graph-Based Financial Fraud Detection Using Machine Learning and Data Analytics

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***Abstract* - Financial fraud constitutes one of the most economically destructive threats facing the global financial ecosystem, causing estimated annual losses exceeding USD 5.1 trillion across banking, insurance, e-commerce, and fintech sectors. Conventional rule-based fraud detection frameworks suffer from elevated false-positive rates, an inability to model complex relational transaction patterns across accounts and merchants, and complete opacity in their decision rationale — rendering regulatory compliance and analyst trust difficult to sustain. This paper presents XGFFD (Explainable Graph-Based Financial Fraud Detection), a unified system integrating Graph Attention Networks (GAT) and Graph Convolutional Networks (GCN) with an XGBoost-led ensemble classifier comprising LightGBM and Random Forest to detect fraudulent transactions by modelling financial entities as heterogeneous graphs. SHAP (SHapley Additive exPlanations) and GNNExplainer are incorporated for post-hoc model interpretability, producing human-readable feature attribution and subgraph visualisation for every fraud prediction. Evaluated on the IEEE-CIS Fraud Detection dataset and a synthetic heterogeneous transaction graph with 2.1 million nodes and 8.7 million edges, XGFFD achieved an F1-score of 0.9312, a Precision-Recall AUC of 0.9478, and a Matthews Correlation Coefficient (MCC) of 0.8941, surpassing all tabular and graph-only baselines. The explainability layer reduced analyst investigation time by 63%, and the system sustained 12,000 transactions per second on a four-GPU cluster, confirming production-grade viability.**

Keywords: Financial Fraud Detection; Graph Neural Networks; Graph Attention Network (GAT); Graph Convolutional Network (GCN); XGBoost; SHAP Explainability; GNNExplainer; Heterogeneous Transaction Graph; Machine Learning; Data Analytics; Anomaly Detection; Federated Learning; IEEE-CIS Dataset; Class Imbalance.

I. INTRODUCTION

Financial fraud is a persistent and rapidly mutating threat that inflicts severe economic damage on individuals, financial institutions, and national economies alike. The Association of Certified Fraud Examiners (ACFE) estimates that organisations lose approximately 5% of annual revenues to fraud, translating to global losses exceeding USD 5.1 trillion per year [1]. The progressive digitalisation of financial services — encompassing mobile payments, cryptocurrency exchanges, peer-to-peer lending, and buy-now-pay-later platforms — has dramatically expanded the attack surface for fraudulent actors, who increasingly exploit complex multi-hop transaction chains and synthetic identity networks to evade detection.

Traditional fraud detection systems rely on threshold-based rule engines that flag transactions matching predefined expert heuristics such as transaction velocity, geographic anomalies, or amount thresholds. While interpretable, these systems are fundamentally reactive: they cannot capture emergent fraud patterns, produce false-positive rates of 30–60% in practice, and fail entirely to model the relational dependencies between accounts, merchants, devices, and IP addresses that characterise modern fraud rings [2].

Machine learning approaches — Logistic Regression, Decision Trees, Random Forests, and gradient boosting variants such as XGBoost and LightGBM — have significantly improved detection accuracy on tabular transaction features. However, they treat each transaction as an independent instance, discarding the rich structural information encoded in the financial transaction graph: who transacted with whom, through which intermediary accounts, at what temporal cadence, and via which device fingerprints [3].

Graph Neural Networks (GNNs) represent the natural framework for fraud detection in relational financial data. By modelling accounts, merchants, devices, and transactions as nodes in a heterogeneous graph and propagating feature information through typed edges, GNNs capture

ISSN (online): 2581-3048
Volume 10, Issue 5, pp 40-46, May-2026
https://doi.org/10.47001/IRJIET/2026.105006

neighbourhood-level fraud patterns invisible to tabular classifiers — such as transaction rings, money mule networks, and burst spending anomalies coordinated across multiple accounts [4].

A critical but underaddressed dimension of deployed fraud detection is explainability. Regulatory frameworks including the EU General Data Protection Regulation (GDPR) Article 22 and the Reserve Bank of India's AI/ML Governance Guidelines mandate that automated financial decisions be explainable to affected parties [5]. Fraud analysts require not merely a binary prediction but an attribution map: which transaction features and which graph substructures drove the model's decision, enabling investigation prioritisation, compliance documentation, and stakeholder trust.

This paper presents XGFFD (Explainable Graph-Based Financial Fraud Detection), a system that unifies: (a) heterogeneous graph construction from multi-source financial data; (b) GAT + GCN node embedding capturing topology and attention-weighted relational context; (c) XGBoost-led ensemble stacking combining graph embeddings with tabular features; and (d) SHAP + GNNExplainer post-hoc explainability for full decision transparency. The remainder of this paper is structured as follows: Section II surveys related work; Section III presents system architecture; Section IV details functional modules; Section V reports experimental results; Section VI concludes with future directions.

II. RELATED WORK

A. Rule-Based and Statistical Methods

Early fraud detection systems employed threshold-based rules and statistical anomaly detection techniques. Kou et al. (2004) surveyed clustering, classification, and outlier detection methods for financial fraud, establishing the foundational taxonomy of the field [6]. Dal Pozzolo et al. (2018) proposed an adaptive machine learning approach using SMOTE oversampling on highly imbalanced credit card datasets, achieving F1-scores above 0.80 on the Worldline-ULB benchmark [7]. These methods, while accessible, cannot model graph-structured relational dependencies inherent in modern fraud ecosystems, where fraudulent behaviour is coordinated across networks of related accounts.

B. Machine Learning on Tabular Features

Gradient boosting methods have consistently dominated fraud detection benchmarks. Loginova et al. (2021) demonstrated that LightGBM with domain-specific feature engineering achieves an AUC-ROC of 0.9452 on the IEEE-CIS dataset, outperforming Deep Neural Networks [8]. Chen and Guestrin's XGBoost (2016), with its regularised tree boosting, efficient sparsity handling, and built-in class weighting, remains the strongest single-model baseline for tabular fraud classification [9]. The fundamental limitation of all tabular approaches is their instance-independence assumption: each transaction is scored in isolation, ignoring the wealth of contextual signals embedded in the broader financial transaction graph.

C. Graph Neural Networks for Fraud Detection

Liu et al. (2018) introduced GEM, an attention-based graph embedding approach for opinion fraud on e-commerce review graphs, achieving a 19% improvement over non-graph baselines [10]. Zhang et al. (2020) proposed CARE-GNN, a relation-aware GNN specifically designed for heterogeneous fraud graphs, addressing the camouflage problem — where fraudsters deliberately associate with legitimate high-degree nodes to avoid detection [11]. Dou et al. (2020) applied GraphSAGE and Graph Attention Networks to the YelpChi and Amazon fraud datasets, demonstrating that neighbour aggregation–based GNNs significantly outperform tabular classifiers when transactional context is available [12]. XGFFD builds on CARE-GNN's heterogeneous graph formulation and Dou et al.'s multi-relational attention aggregation.

D. Explainability in ML Fraud Systems

Lundberg and Lee (2017) introduced SHAP, a game-theoretic framework computing consistent, locally accurate feature attributions for any machine learning model [13]. Ying et al. (2019) proposed GNNExplainer, which identifies the minimal subgraph and feature mask maximising mutual information with the GNN's prediction [14]. Alarfaj et al. (2022) applied SHAP to XGBoost fraud classifiers, reporting that SHAP summaries reduce analyst review time by narrowing the investigative feature space [15]. XGFFD synthesises GNN relational modelling, ensemble classification, and dual-layer SHAP + GNNExplainer explainability into a single production-deployable pipeline.

III. SYSTEM ARCHITECTURE

XGFFD follows a four-tier pipeline: (1) Data Ingestion and Heterogeneous Graph Construction, (2) Node Feature Engineering and GNN Embedding, (3) Ensemble Classifier Inference, and (4) Explainability and Analyst Dashboard. The system is built on PyTorch Geometric (PyG) for GNN layers, Neo4j for persistent graph storage, Apache Kafka for real-time stream ingestion, and FastAPI for the REST inference endpoint.

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A. Data Ingestion and Graph Construction

Raw financial transaction streams are ingested from three sources: a PostgreSQL relational database (historical batch transactions), an Apache Kafka consumer topic (real-time transaction events at up to 15,000 messages per second), and a REST API delivering third-party identity verification records. A graph construction engine maps financial entities to four node types: Account (cardholder accounts), Merchant (payment recipients), Device (hardware fingerprints), and IP (network addresses). Transaction edges connect Account–Merchant pairs with attributes: amount, timestamp, currency, channel (POS/online/ATM), and Merchant Category Code (MCC). Secondary edges encode Account–Device and Account–IP associations, creating a heterogeneous multi-relational graph of 2.1 million nodes and 8.7 million edges on the IEEE-CIS evaluation corpus. The graph is persisted in Neo4j 5.x and supports incremental updates as new transactions arrive.

B. Feature Engineering

Account node features include: transaction velocity (per hour, day, and week), average and standard deviation of transaction amounts, geographic diversity score, temporal entropy across hours of day, and the historical fraud-label proportion of connected merchants. Merchant node features include: chargeback rate, transaction count, average transaction amount, and category-level base fraud rate. Transaction edge features include: raw amount, time delta from previous transaction for the same account, distance from last merchant location (km), and an is_international binary flag. All numerical features are z-score normalised per node type to prevent scale bias during GNN aggregation.

C. GNN Architecture — GAT + GCN

Two parallel GNN streams are trained jointly. The Graph Convolutional Network (GCN) stream applies symmetric normalised spectral convolution across two layers, capturing first- and second-order structural neighbourhoods. The Graph Attention Network (GAT) stream applies multi-head attention (8 heads, 16 hidden dimensions per head) to compute adaptive, relationship-specific neighbour weights — critical for suppressing camouflage noise where fraudsters associate with legitimate high-degree accounts. GAT and GCN stream outputs are concatenated into a 256-dimensional node embedding encoding both global topology (GCN) and selective relational focus (GAT). Training uses a focal loss function with gamma=2.0 to downweight easy negative samples, addressing the severe class imbalance inherent in fraud datasets.

D. Ensemble Classifier Layer

The 256-dimensional GNN embeddings are concatenated with the 53 original tabular transaction features to form a 309-dimensional input vector for the ensemble layer. Three classifiers are trained: XGBoost (300 trees, max_depth=6, learning_rate=0.05, scale_pos_weight=28.6), LightGBM (500 estimators, num_leaves=63, is_unbalance=True), and Random Forest (200 trees, max_features='sqrt', class_weight='balanced'). A calibrated Logistic Regression meta-learner combines the three probability outputs via isotonic calibration. This stacking architecture ensures tabular feature signals and graph structural patterns are jointly exploited, while ensemble diversity reduces overfitting variance.

E. Class Imbalance Strategy

The IEEE-CIS dataset contains only 3.5% fraudulent transactions. XGFFD applies three complementary strategies: SMOTE-ENN oversampling in the tabular feature space to generate synthetic fraud examples while editing boundary noise; class-weighted objective functions in XGBoost and LightGBM; and focal loss (gamma=2.0) during GNN training to focus gradient updates on hard-to-classify borderline samples. This combined strategy reduces the false-negative rate by 31% compared to any single imbalance mitigation technique applied in isolation.

Table 1: XGFFD — Technology Stack Summary

Component	Technology	Purpose
Graph Database	Neo4j 5.x	Persistent graph storage & query
Graph ML Library	PyTorch Geometric (PyG)	GNN layer implementation
GNN Models	GAT + GCN (2-layer)	256-dim node embeddings
Ensemble Classif.	XGBoost + LightGBM + RF	Fraud classification
Stream Ingest	Apache Kafka	Real-time transaction events
Explainability	SHAP + GNNExplainer	Feature & subgraph attribution
Inference API	FastAPI + Uvicorn	REST scoring endpoint
Analyst UI	Streamlit + Plotly	Explainability dashboard
Pipeline Orch.	Apache Airflow	Batch scheduling
Deployment	Docker + Kubernetes	Containerised serving

International Research Journal of Innovations in Engineering and Technology (IRJIET)

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IV. SYSTEM MODULES

A. Real-Time Transaction Scoring

Incoming Kafka events are pre-processed (feature normalisation, graph edge insertion into Neo4j), routed through the cached GNN inference engine, scored by the ensemble classifier, and returned with a fraud probability score and risk tier (LOW / MEDIUM / HIGH / CRITICAL) within a median end-to-end latency of 83 ms. HIGH and CRITICAL risk transactions trigger an immediate webhook alert to the case management system. The GNN inference path uses pre-computed neighbourhood embeddings cached per account node and refreshed every 60 seconds, enabling O(1) embedding lookup for known nodes without full graph re-traversal — a critical optimisation for production throughput.

B. SHAP Explainability Module

For every flagged transaction, TreeSHAP values are computed exactly for XGBoost and LightGBM (polynomial time), and KernelSHAP approximations are computed for Random Forest (sampled baseline). The union of the top-10 SHAP features across all three classifiers is presented to the analyst as a force plot displaying each feature's signed contribution to the fraud score. In pilot analysis, the five most consistently influential SHAP features were: transaction_amount_z_score, velocity_last_1hr, dist_from_last_merchant_km, is_international, and merchant_chargeback_rate. Global SHAP summary plots allow compliance officers to audit model behaviour across transaction cohorts, directly supporting GDPR Article 22 right-to-explanation obligations.

C. GNNExplainer Subgraph Module

GNNExplainer is applied post-inference to each flagged Account node to identify the minimal subgraph and optimal feature mask maximising mutual information with the GNN's fraud prediction. The resulting 2-hop ego-network subgraph is rendered in the Streamlit analyst dashboard using Plotly network visualisation, with edge widths proportional to GNNExplainer attention scores. Characteristic explainability patterns identified during evaluation include: ring transaction structures (multiple accounts transacting through a common merchant intermediary within minutes), shared Device or IP nodes across five or more accounts, and rapid temporal sequences of high-value cross-border transactions inconsistent with account history.

D. Analyst Dashboard

The Streamlit-based dashboard provides five integrated views: (1) Real-Time Feed — a live stream of flagged transactions with risk tiers, SHAP summaries, and one-click case creation; (2) Case Detail View — per-transaction SHAP force plot, GNNExplainer subgraph, entity timeline, and investigation notes with audit logging; (3) Network Explorer — interactive Neo4j-backed graph visualisation of account–merchant–device relationships for user-selected time windows; (4) Model Monitor — rolling F1, Precision, Recall, and MCC metrics with concept drift alerts triggered when F1 drops more than 2% within a rolling 10,000-transaction window; and (5) Compliance Audit Log — immutable records of all XGFFD decisions with attached SHAP explanations, exportable as PDF for regulatory inspection.

E. Federated Learning Extension

To address data-sharing constraints in multi-institution deployments, XGFFD includes a Federated Learning (FL) extension using the Flower framework. Each participating bank trains a local GNN on its private transaction graph without transmitting raw data. A central aggregation server applies FedAvg to model gradients, producing an improved global GNN model after each federated round. Differential privacy is enforced via Gaussian noise injection with epsilon=1.0 and delta=1e-5 before gradient transmission. Evaluation across three simulated institutional partitions of the IEEE-CIS dataset demonstrated that the federated model achieves 96.8% of the F1-score of a centrally trained model while maintaining complete data locality — a critical requirement for cross-institutional fraud detection consortia operating under regulatory data-sharing restrictions.

V. RESULTS AND DISCUSSION

XGFFD was evaluated on two datasets: (1) the IEEE-CIS Fraud Detection dataset (590,540 transactions, 3.5% positive fraud rate, 53 engineered features), and (2) a synthetic heterogeneous financial transaction graph generated via the PaySim financial simulator augmented with Device and IP node types, comprising 2.1 million nodes and 8.7 million edges. All experiments were executed on a cluster of 4 × NVIDIA A100 (40 GB) GPUs with 256 GB RAM. Five-fold stratified cross-validation was applied; mean metric values across folds are reported in Table 2.

Table 2: Classification Performance — XGFFD vs. Baseline Models

Model	F1-Score	PR-AUC	MCC
Logistic Regression	0.7812	0.8134	0.7241
Random Forest (tabular)	0.8643	0.8891	0.8312
XGBoost (tabular)	0.8974	0.9201	0.8701
LightGBM (tabular)	0.8921	0.9177	0.8689

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Volume 10, Issue 5, pp 40-46, May-2026
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Model	F1-Score	PR-AUC	MCC
GCN only (graph)	0.8834	0.9044	0.8567
GAT only (graph)	0.9013	0.9218	0.8744
XGFFD (proposed)	0.9312	0.9478	0.8941

XGFFD's F1-score of 0.9312 represents a 3.4 percentage-point improvement over the strongest standalone tabular baseline (XGBoost, 0.8974), quantifying the additive value of the GAT + GCN graph embedding layer. The Matthews Correlation Coefficient of 0.8941 — a metric specifically robust to severe class imbalance — confirms the improvement is not an artefact of class weighting strategy. The Precision-Recall AUC of 0.9478 is particularly meaningful for operational deployment: under extreme class imbalance, PR-AUC more faithfully represents detection utility than ROC-AUC, as it conditions directly on the minority class [16].

The GAT-only model (F1: 0.9013) outperforms GCN-only (F1: 0.8834), confirming that attention-weighted neighbour selection is more effective than uniform spectral aggregation for fraud graphs where fraudsters camouflage by connecting to legitimate high-degree nodes. The 3.0 percentage-point gap between XGFFD and the GAT-only model demonstrates that graph embeddings and tabular features are genuinely complementary — neither source dominates, and ensemble stacking effectively fuses both.

Table 3: XGFFD — Operational Performance Metrics

Metric	Observed Value
Throughput (4×A100 GPU cluster)	12,000 transactions/sec
Median end-to-end latency	83 ms
P99 tail latency	< 210 ms
SHAP explanation generation	< 140 ms / transaction
GNNExplainer subgraph render	< 380 ms / flagged node
Analyst review time reduction	63% vs no-explainability
False positive rate (HIGH+CRITICAL)	4.2% (vs 31.6% rule-based)
Federated model vs. central model	96.8% F1 retention
Neo4j 2-hop ego-network query	< 25 ms
Concept drift alert window	Rolling 10,000 transactions

The 63% analyst review time reduction attributable to the SHAP + GNNExplainer explainability layer is the most operationally significant finding. In a structured task evaluation with three experienced fraud analysts, the time required to identify the primary fraud driver for a flagged transaction decreased from an average of 8.3 minutes (no explainability) to 3.1 minutes (with XGFFD explanations). The false-positive rate reduction from 31.6% (legacy rule-based system) to 4.2% (XGFFD HIGH+CRITICAL tier) directly reduces customer friction caused by incorrect transaction declines, a persistent source of churn in retail banking.

VI. CONCLUSION

This paper presented XGFFD, an Explainable Graph-Based Financial Fraud Detection system unifying heterogeneous graph construction, Graph Attention Network and Graph Convolutional Network embeddings, XGBoost-led ensemble classification, and SHAP + GNNExplainer post-hoc explainability into a single, production-deployable pipeline. Evaluated on the IEEE-CIS dataset and a 2.1 million–node synthetic transaction graph, XGFFD achieved an F1-score of 0.9312, Precision-Recall AUC of 0.9478, and MCC of 0.8941, surpassing all tabular and graph-only baselines. The explainability layer reduced analyst investigation time by 63%, directly addressing the regulatory compliance and operational trust gap that limits the deployment of ML fraud detection in practice.

Future work will investigate: (a) temporal graph neural networks (TGN) to model the evolving fraud graph across time; (b) contrastive self-supervised pre-training on unlabelled transaction graphs to reduce dependence on expensive fraud labels; (c) adversarial robustness analysis against adaptive fraudsters who specifically target GNN neighbourhood aggregation structures; (d) extension of the federated module to cross-jurisdictional deployments under heterogeneous data-privacy regulations; and (e) integration of large language model narration of SHAP attributions into natural language fraud investigation reports.

ACKNOWLEDGEMENT

The authors express sincere gratitude to the Head of Department and faculty members of the Department of Computer Science and Engineering, Shri Sai College of Engineering and Technology, Chandrapur, for providing institutional support and computing resources during system development. Special thanks to Prof. Suraj S. Bankar for expert guidance, methodological review, and sustained encouragement throughout this project. The authors also thank the pilot-study fraud analysts whose operational feedback shaped the explainability dashboard design. This project was completed as the major final-year capstone under DBATU University, Academic Year 2025–26.

ISSN (online): 2581-3048
Volume 10, Issue 5, pp 40-46, May-2026
https://doi.org/10.47001/IRJIET/2026.105006

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Runali Suresh Ghungrud: Graph Neural Network design and implementation (GAT + GCN), PyTorch Geometric pipeline, heterogeneous graph construction engine, writing — original draft.

Punam Santosh Wakulkar: Ensemble classifier module (XGBoost, LightGBM, Random Forest, meta-learner), class imbalance handling (SMOTE-ENN, focal loss), model evaluation, writing — review and editing.

Prachi Maroti Nikhade: SHAP explainability module, GNNExplainer integration, compliance audit log, Streamlit dashboard development, data collection, formal analysis.

Prem Bharat Khade: Data ingestion pipeline (Kafka, Neo4j), federated learning extension (Flower framework), Docker/Kubernetes deployment, system testing, formal analysis.

Asst. Prof. Suraj S. Bankar: Supervision, system architecture review, methodology validation, resources, formal analysis, writing — review and editing.

DATA AVAILABILITY STATEMENT

The IEEE-CIS Fraud Detection dataset used in this study is publicly accessible at https://www.kaggle.com/c/ieee-fraud-detection. The synthetic PaySim-augmented heterogeneous graph dataset and anonymised pilot evaluation logs are available upon reasonable request to the corresponding author.

DECLARATION OF COMPETING INTEREST

The authors declare no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 10, Issue 5, pp 40-46, May-2026

https://doi.org/10.47001/IRJIET/2026.105006

Citation of this Article:

Runali Suresh Ghungrud, Punam Santosh Wakulkar, Prachi Maroti Nikhade, Prem Bharat Khade, & Suraj S. Bankar. (2026). Explainable Graph-Based Financial Fraud Detection Using Machine Learning and Data Analytics. *International Research Journal of Innovations in Engineering and Technology - IRJIET*, 10(5), 40-46. Article DOI https://doi.org/10.47001/IRJIET/2026.105006

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