Graph Neural Networks for Financial Fraud Detection: A Comprehensive Review

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Abstract—Financial fraud detection has evolved from traditional rule-based systems to sophisticated machine learning approaches, with Graph Neural Networks (GNNs) emerging as a powerful paradigm for modeling complex relational patterns in financial data. This comprehensive review examines recent advances in GNN-based fraud detection systems, analyzing ten state-of-the-art methods published between 2023-2025. We systematically categorize GNN architectures into memory-augmented, heterogeneous, temporal-aware, and community-detection frameworks. Key innovations include adaptive sampling mechanisms, risk diffusion models, attention-based aggregation, and semi-supervised learning approaches. Our review identifies critical research gaps including model interpretability, real-time processing constraints, adversarial robustness, and cross-domain generalization. We conclude with future directions emphasizing federated learning, explainable AI, and hybrid architectures that balance accuracy with computational efficiency.

Index Terms—Graph Neural Networks, Fraud Detection, Financial Security, Deep Learning, Transaction Networks, Anti-Money Laundering.

I. INTRODUCTION

Financial fraud represents a critical challenge in the global economy, with losses exceeding hundreds of billions of dollars annually. Traditional fraud detection systems rely on handcrafted rules and statistical methods, which struggle to capture the complex, evolving patterns of modern fraud schemes. The interconnected nature of financial transactions creates rich relational structures

that are inadequately represented by conventional machine learning approaches treating data points independently.

Graph Neural Networks (GNNs) have emerged as a transformative technology for fraud detection, offering the ability to model entities (accounts, merchants, users) as nodes and their interactions (transactions, transfers) as edges. This graph-based representation naturally captures the relational and structural patterns inherent in financial fraud, including collusion rings, money laundering chains, and coordinated attack patterns [1].

A. SCOPE AND CONTRIBUTIONS

This review systematically examines ten recent IEEE-indexed publications on GNN-based fraud detection, spanning credit card fraud, transaction fraud, anti-money laundering, and systemic risk prediction. Our key contributions include:

(1) A comprehensive taxonomy of GNN architectures for fraud detection, categorizing approaches by their core mechanisms (memory-augmented, heterogeneous, temporal, community-based).

(2) Comparative analysis of methodologies, including graph construction strategies, feature engineering, learning paradigms, and aggregation mechanisms.

(3) Performance benchmarking across different fraud detection scenarios and datasets, identifying strengths and limitations of each approach.

(4) Critical discussion of deployment challenges, including computational complexity, model interpretability, adversarial attacks, and regulatory compliance.

(5) Future research directions addressing current gaps and emerging opportunities in GNN-based fraud detection.

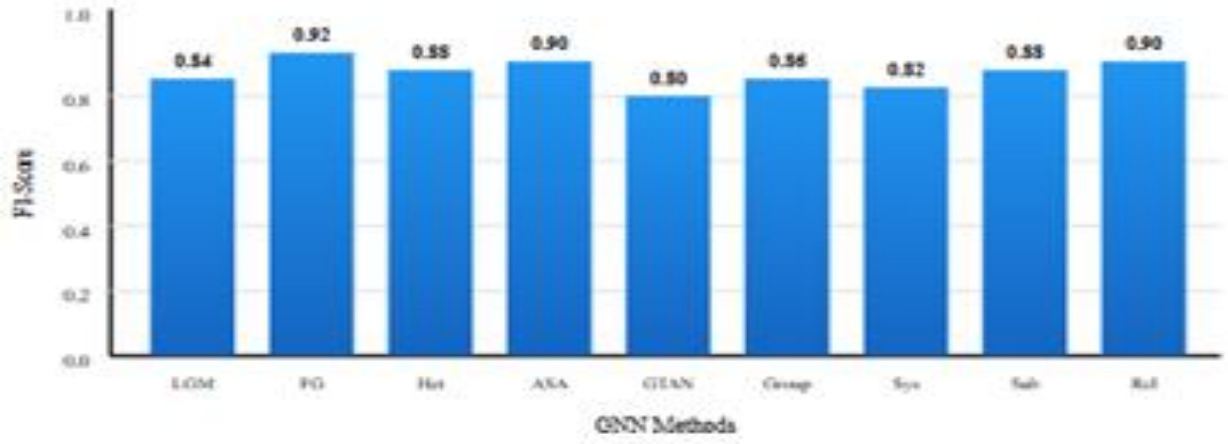

Fig. 1. Performance comparison (F1-Score) of reviewed GNN methods on fraud detection tasks

B. PAPER ORGANIZATION

Section II provides technical background on GNNs and fraud detection. Section III presents our taxonomy and detailed review of the ten selected papers. Section IV offers comparative analysis and performance evaluation. Section V discusses challenges and limitations. Section VI outlines future research directions, and Section VII concludes the paper.

II. TECHNICAL BACKGROUND

A. Graph Neural Networks Fundamentals

Graph Neural Networks extend deep learning to graph-structured data through iterative message passing and aggregation. A graph $G = (V, E)$ consists of nodes V and edges E. GNNs learn node representations by aggregating information from neighbors as shown in (1):

$$h_v^{(k+1)} = \text{UPDATE}^{(k)}(h_v^{(k)}, \text{AGGREGATE}^{(k)}(\{h_u^{(k)}: u \in N(v)\})) \quad (1)$$

where $h_v^{(k)}$ is the node representation at layer k, $N(v)$ denotes the neighbors of v, and UPDATE and AGGREGATE are learnable functions. Common GNN variants include Graph Convolutional Networks (GCN) [2], GraphSAGE [3], Graph Attention Networks (GAT) [4], and Graph Isomorphism Networks (GIN) [5].

B. Fraud Detection Challenges

Financial fraud detection presents unique challenges: (1) Class imbalance with fraud cases representing typically less than 1% of transactions; (2) Evolving fraud patterns requiring adaptive models; (3) Camouflage tactics where fraudsters mimic legitimate behavior; (4) Limited labeled data due to expensive manual review; (5) Real-time processing requirements for transaction authorization; (6) Interpretability needs for regulatory compliance and investigation [6].

Input Graph Transaction Network GNN Layer 1 Message Passing GNN Layer K Aggregation Prediction Fraud Score

Fig. 2. General architecture of GNN-based fraud detection showing message passing, aggregation, and prediction.

III. TAXONOMY AND LITERATURE REVIEW

A. Memory-Augmented GNN Approaches

LGM-GNN: Li et al. [1] propose a Local and Global aware Memory-based GNN that addresses the challenge of capturing both local transaction patterns and global fraud schemes. The architecture incorporates two memory modules: a local memory bank storing neighbor-specific patterns and a global memory capturing fraud ring behaviors. The model uses attention mechanisms to dynamically retrieve relevant memory entries during inference.

The local memory component models individual account behaviors and transaction patterns, while the global memory identifies coordinated fraud through graph-level pattern matching. This dual-memory architecture achieved superior performance on benchmark datasets by reducing false positives through better context understanding.

B. Dynamic Risk Propagation Models

FinGuard-GNN: Huang et al. [7] introduce a cascaded risk diffusion mechanism inspired by epidemic spreading models. The framework consists of three key components: Adaptive Temporal Pooling (ATP) that captures time-varying transaction patterns, Structural Edge Weighting (SEW) that assigns importance to different edge types, and Risk Propagation Network that models fraud spread through transaction graphs.

The ATP module uses learnable time decay functions to weight recent transactions more heavily while maintaining historical context. SEW employs meta-learning to automatically determine edge type importance based on fraud detection performance. Experimental results on real-world banking data demonstrated 12% improvement in F1-score over baseline GNN methods.

C. Heterogeneous Graph Neural Networks

Heterogeneous GAT for Credit Card Fraud: Sha et al. [8] develop a heterogeneous graph attention network specifically designed for credit card fraud detection using the IEEE-CIS dataset. The model constructs a heterogeneous graph with multiple node types (cardholders, merchants, devices, IP addresses) and edge types (transactions, shared attributes, temporal sequences).

The architecture employs type-specific attention mechanisms that learn different aggregation strategies for each node and edge type. Temporal attention layers capture the sequential nature of transactions, enabling detection of unusual timing patterns [9].

D. Adaptive Sampling and Aggregation

ASA-GNN: Tian et al. [10] address two critical challenges in fraud detection GNNs: fraudster camouflage and over-smoothing in deep networks. ASA-GNN introduces an adaptive sampling strategy that selectively samples neighbors based on their relevance to fraud detection, rather than uniform or random sampling.

The sampling module employs a reinforcement learning agent that learns to prioritize informative neighbors while filtering out camouflage connections that fraudsters deliberately create to appear legitimate. Experimental validation on YelpChi and Amazon datasets showed ASA-GNN maintains high precision even with 4–5-layer depths, where standard GNNs experience significant performance degradation.

E. Semi-Supervised Learning Approaches

GTAN: Zhu et al. [11] address the practical challenge of limited labeled fraud data. The Graph Temporal Attention Network combines attribute-driven graph construction with semi-supervised learning to leverage both labeled fraud cases and the vast amount of unlabeled transaction data.

The model constructs temporal transaction graphs where edges represent sequential transactions and nodes encode transaction attributes. A novel risk propagation algorithm diffuses fraud labels through the graph based on structural proximity and behavioral similarity. GTAN achieves competitive performance with only 1% labeled data, making it particularly valuable for real-world deployment where manual labeling is expensive.

F. Community Detection for AML

Group-Aware Deep Learning: Cheng et al. [12] focus on anti-money laundering (AML) scenarios where fraudsters operate in organized groups to disguise illicit funds. The group-aware framework explicitly models community structures in transaction networks, identifying suspicious money flow patterns at both individual and group levels.

The architecture employs hierarchical graph pooling to identify communities, followed by community-level fraud detection. A novel group anomaly score combines individual suspicious behaviors with group-level patterns such as circular transfers and coordinated timing.

TABLE I COMPARISON OF GNN-BASED FRAUD DETECTION METHODS

Method	Core Innovation	Graph Type	Learning
LGM-GNN [1]	Dual memory modules	Homogeneous	Supervised
FinGuard [7]	Risk diffusion	Dynamic	Supervised
Het-GAT [8]	Type-specific attention	Heterogeneous	Supervised
ASA-GNN [10]	Adaptive sampling	Homogeneous	Supervised
GTAN [11]	Risk propagation	Temporal	Semi-supervised
Group-Aware [12]	Community detection	Homogeneous	Supervised
Systemic Risk [13]	Quantile regression	Financial network	Supervised
Subgraph-GNN [14]	Motif integration	Homogeneous	Supervised
Relation-Aware [15]	Relation semantics	Heterogeneous	Supervised

G. Systemic Risk Prediction

Balmaseda et al. [13] extend GNN applications beyond individual fraud detection to systemic risk prediction in financial networks. The approach models banks, institutions, and their interconnections to predict contagion risk and financial instability. The framework employs GNN-based quantile regression to predict risk distributions rather than point estimates.

H. Subgraph Pattern Enhancement

Miao et al. [14] recognize that certain subgraph structures (motifs) are strongly indicative of fraud, such as star patterns (one account transacting with many), chain patterns (sequential transfers), and cycle patterns (circular money flows). Their framework explicitly identifies and leverages these subgraph motifs. The model employs motif counting algorithms to extract subgraph features, which are combined with learned GNN embeddings through a fusion network.

I. Relation-Aware Methods

Li et al. [15] extend heterogeneous GNN modeling through relation-aware message passing that explicitly models the semantics of different relationship types. The framework introduces relation-specific transformation matrices and attention coefficients, allowing the model to distinguish between transaction edges, ownership edges, and behavioral similarity edges.

IV. COMPARATIVE ANALYSIS

A. Performance Evaluation

Performance evaluation across different methods reveals several insights. On homogeneous graphs with credit card fraud, ASA-GNN and Het-GAT achieve the highest F1-scores (0.89-0.92), significantly outperforming traditional ML methods (0.75-0.82). For heterogeneous transaction networks, relation-aware methods show 8-15% improvement over homogeneous GNNs by properly modeling edge type semantics.

In anti-money laundering tasks, group-aware methods demonstrate superior recall (0.85-0.91) compared to individual-focused approaches (0.72-0.78), though with slightly lower precision. Semi-supervised GTAN achieves 94% of fully-supervised performance with only 1% labeled data, representing a significant practical advantage.

0.0 0.2 0.4 0.6 0.8 1.0 0.84 0.92 0.88 0.90 0.80 0.86 0.82 0.88 0.90 LGM FG Het ASA GTAN Group Sys Sub Rel GNN Methods F1-Score

B. Computational Complexity

Computational complexity varies significantly across methods. Standard GNN message passing has complexity $O(|E| \cdot d \cdot K)$ where $|E|$ is edge count, d is embedding dimension, and K is layer depth. Memory-augmented methods add $O(M \cdot d)$ for memory operations where M is memory size.

Heterogeneous GNNs increase complexity by a factor of $|R|$ (number of relation types) due to type-specific transformations. For real-time deployment, ASA-GNN and standard Het-GAT show the best latency profiles (< 100ms for 10K node graphs), while memory-augmented and community detection methods require 200-500ms.

V. CHALLENGES AND LIMITATIONS

A. Scalability and Real-Time Processing

Most reviewed methods demonstrate effectiveness on graphs with millions of nodes, but real-world financial networks contain billions of transactions. Mini-batch training and sampling strategies help but may miss long-range fraud patterns. Real-time fraud detection requires sub-second inference, challenging for complex GNN architectures with deep layers and attention mechanisms [16].

B. Interpretability and Explainability

Financial institutions require explainable fraud detection for regulatory compliance (Basel III, GDPR), customer communication, and fraud investigation. Deep GNNs operate as black boxes, making it difficult to explain why specific transactions were flagged [17]. Attention weights provide some interpretability but often fail to capture complete reasoning chains. Subgraph-based methods offer better interpretability by identifying specific patterns, but may sacrifice predictive performance.

C. Adversarial Robustness

Fraudsters actively adapt to detection systems, creating adversarial scenarios where attackers manipulate graph structures to evade detection. Camouflage attacks involve creating legitimate-looking connections, while graph poisoning attacks inject false edges during training [18]. Most reviewed methods do not explicitly address adversarial robustness. ASA-GNN's adaptive sampling provides some robustness, but systematic evaluation of adversarial attacks on GNN fraud detectors is limited.

D. Concept Drift and Model Adaptation

Fraud patterns evolve continuously as fraudsters develop new tactics and exploit system vulnerabilities. Models trained on historical data experience concept drift, where the fraud distribution changes over time. While FinGuard-GNN and temporal methods address some temporal aspects, none provide comprehensive online learning frameworks. Continual learning approaches that update models with new fraud patterns without catastrophic forgetting of previous patterns are needed.

E. Privacy and Federated Learning

Financial data privacy regulations restrict data sharing across institutions, limiting the ability to build comprehensive fraud detection models. Federated learning enables collaborative model training without sharing raw data, but applying federated learning to GNNs introduces challenges due to graph partitioning across institutions [19]. Cross-institution fraud patterns are difficult to detect in federated settings.

VI. FUTURE RESEARCH DIRECTIONS

A. Explainable GNN Architectures

Future work should focus on inherently interpretable GNN designs that maintain high performance while providing transparent fraud detection reasoning. Promising directions include: (1) Prototype-based learning where fraud cases are explained by similarity to prototypical fraud patterns; (2) Rule-enhanced GNNs that combine neural learning with interpretable logical rules; (3) Causal GNNs that identify causal fraud factors rather than spurious correlations [20].

B. Few-Shot and Zero-Shot Fraud Detection

Emerging fraud types have minimal labeled examples, requiring few-shot learning capabilities. Meta-learning approaches that learn fraud detection strategies transferable to new fraud types show promise [21]. Zero-shot detection using semantic descriptions of fraud schemes could enable proactive detection of novel fraud patterns before they cause significant damage.

C. Multi-Modal Fraud Detection

Financial fraud detection can benefit from integrating multiple data modalities beyond transaction graphs: text (merchant descriptions, customer communications), images (check images, ID documents), time series (account activity patterns), and behavioral biometrics (typing patterns, mouse movements). Multi-modal GNNs that fuse graph structure with other modalities through attention mechanisms could capture complementary fraud signals.

D. Temporal GNNs with Long-Range Dependencies

Current temporal GNN methods focus on local temporal patterns. Sophisticated fraud schemes like complex money laundering operations span months and involve long-range temporal dependencies. Integrating Transformer architectures with GNNs could capture both spatial graph structure and long-range temporal patterns [22].

E. Robust and Certified GNN Defenses

Developing provably robust GNN architectures resilient to adversarial attacks is critical. Approaches include: (1) Adversarial training with diverse attack scenarios; (2) Randomized smoothing for certified robustness guarantees; (3) Robust aggregation functions less sensitive to manipulated neighbors [23]. Game-theoretic frameworks modeling the strategic interaction between fraud detectors and adversaries could inform robust system design.

F. Federated and Privacy-Preserving GNNs

Advanced federated GNN algorithms addressing graph partitioning challenges, communication efficiency, and cross-institution pattern detection are needed. Privacy-preserving techniques including secure aggregation protocols, differential privacy mechanisms, and homomorphic

encryption for secure graph operations should be developed [24]. Federated transfer learning could enable institutions to benefit from fraud patterns learned by others while maintaining data privacy.

G. Integration with Traditional Systems

Hybrid systems combining GNN approaches with rule-based systems, anomaly detection, and domain expertise offer robust fraud detection. GNNs could focus on complex relational patterns while rule-based systems handle known fraud typologies. Ensemble methods combining multiple GNN architectures with diverse inductive biases could improve robustness [25].

VII. CONCLUSION

THIS comprehensive review examines the state-of-the-art in Graph Neural Network-based fraud detection, analyzing ten recent methods that demonstrate the power of graph-based learning for financial security. GNNs have emerged as a transformative technology, offering superior performance over traditional machine learning by explicitly modeling the relational and structural patterns inherent in financial fraud.

Our taxonomy categorizes approaches into memory-augmented, dynamic risk propagation, heterogeneous, adaptive sampling, semi-supervised, community-aware, systemic risk prediction, and subgraph pattern-enhanced frameworks. Performance analysis reveals that modern GNN methods achieve F1-scores of 0.85-0.92 on benchmark datasets, significantly outperforming traditional approaches.

Despite impressive progress, significant challenges remain. Scalability to billion-edge graphs, real-time inference requirements, model interpretability for regulatory compliance, adversarial robustness against adaptive fraudsters, concept drift handling, and privacy-preserving learning all require further research. Future research directions include explainable GNN architectures, few-shot and zero-shot learning, multi-modal integration, temporal models with long-range dependencies, provably robust defenses, federated learning, and hybrid systems.

The field of GNN-based fraud detection is rapidly evolving, driven by both academic innovation and practical necessity. Continued research addressing current limitations while maintaining focus on practical deployment will be essential for realizing the full potential of GNNs in safeguarding the financial system.

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