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A Graph Neural Network-Based Approach for Detecting Fraudulent Small-Value High-Frequency Accounting Transactions

ZHANG, Yitian [1*] LIU, Yibang [2] ZHENG, Shuaiqi [3]

[1] UW-Madison, USA
[2] Baruch College, USA
[3] Illinois Institute of Technology, USA

**** ZHANG, Yitian is the corresponding author, E-mail: ethiosusqun8@outlook.com***

Abstract: The growth of digital accounting systems has led to increased fraud schemes, especially those involving small-value businesses. This paper presents a novel neural network architecture to capture order to break it down to break up suitable class and image heterophily in fraud detection by holding different representations for homophilic and heterophilic characteristics, making it more effective in detecting fraud patterns. The model includes a unique system of body-aware construction and adaptive memory to capture complex changes on multiple time scales. We introduce a two-channel feature extraction mechanism that performs similar and different processes independently, facilitating the storage and propagation of fraud signals from the business network. Various experiments on two real-world datasets show that our method significantly improved over the state-of-the-art method, with a performance of 12.3% in AUC -ROC and 15.7% in F1-score. The model is particularly effective in identifying fraud schemes that use multiple accounts and different currencies, achieving a 67% reduction in false positives. Our results show the model can identify subtle transaction patterns that distinguish fraudulent from legitimate transactions.

Keywords: Financial Risk Management, Graph Neural Networks, Fraud Detection, Small-Value Transactions, Temporal-Spatial Patterns.

Disciplines: Finance. **Subjects:** Financial Risk Management.

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1 INTRODUCTION

1.1 RESEARCH BACKGROUND AND MOTIVATION

The rapid development of digital accounting systems and online payment platforms has recently changed the business environment. While these advances improve efficiency, they also create new disadvantages in accounting[1]. Global economic losses from financial fraud continue to rise, with economic fraud causing billions of dollars in losses each year. An important factor in today's accounting fraud is the occurrence of small-value high-frequency transactions, which make it difficult to find because of their subtle nature and high volume.

Small-value high-frequency fraud is a sophisticated form of financial fraud in which perpetrators deliberately divide large transactions into smaller ones to escape the system's standard discovery. These transactions typically fall below conventional monitoring thresholds while maintaining high occurrence frequencies[2]. Traditional rule-based detection methods and classical machine-learning approaches struggle to identify such patterns, mainly when fraudsters employ camouflage techniques to make transactions appear legitimate.

The basic network model of the business enterprise, where the organizations involved in the interaction through various business models, always lends itself to the modeling process. Graph Neural Networks (GNNs) have shown excellent capabilities in capturing complex patterns and relationships in structured data, making them particularly suitable for fraud detection[3]. GNNs' ability to learn representative entities while considering features and topological information provides a valuable framework for identifying fraudulent patterns in sharing.

1.2 RESEARCH CHALLENGES AND PROBLEMS

The detection of fraudulent small-value high-frequency accounting transactions presents several critical challenges. The class imbalance problem remains prominent, with fraudulent transactions constituting only a tiny percentage of total transactions. This imbalance significantly impacts model performance and requires specialized techniques to address[4]. The temporal dynamics of transaction patterns add another layer of complexity, necessitating models that can effectively capture both spatial and temporal dependencies.

Graph heterophily in fraudulent transactions poses a substantial challenge, as fraudulent nodes often connect more frequently with legitimate nodes to avoid detection. Traditional GNN models, designed under the homophily assumption, may not effectively capture these fraudulent patterns[5]. Additionally, the high-dimensional nature of transaction data and missing values in real-world datasets complicate the feature extraction and representation learning processes.

1.3 Research Contributions

This paper proposes a novel GNN-based architecture to detect fraudulent small-value high-frequency accounting transactions. The model incorporates a dual-feature aggregation mechanism that processes and preserves homophilic and heterophilic features, enabling more effective detection of camouflaged fraudulent patterns[6]. A temporal-aware graph construction method is introduced to capture the sequential patterns of high-frequency transactions while maintaining structural information.

The proposed approach introduces an innovative feature separation technique that maintains distinct representations for transaction similarities and dissimilarities, facilitating more nuanced fraud detection. A specialized loss function addresses the class imbalance problem while optimizing the model's performance on minority class detection[7]. Extensive experiments on real-world accounting transaction datasets demonstrate the superior performance of our approach compared to state-of-the-art methods across multiple evaluation metrics.

2 RELATED WORK

2.1 Traditional Methods for Accounting Fraud Detection

Conventional methods for fraud detection are mainly based on rule-based and machine-learning methods. The rule-based approach uses pre-defined criteria and patterns based on expert knowledge to identify suspicious transactions. Statistical methods, including Logistic Regression, Support Vector Machines, and Random Forest, are widely used in fraud detection[8]. This process analyzes business variables such as cost, frequency, and time to identify negative patterns. While these techniques have effectively identified fraud patterns, they cannot capture the relationships and fraud strategies in today's systems.

2.2 Deep Learning Methods in Financial Fraud Detection

Advances in deep learning have brought new perspectives to financial fraud detection. Convolutional Neural Networks (CNNs) have been adapted for data processing processes by converting financial data into models suitable for network processing[9]. Long Short-Term Memory (LSTM) networks effectively store temporal expectations in concatenated data. Deep Autoencoders are employed for anomaly detection by learning compressed representations of traditional business models[10]. These deep learning methods provide improved resource extraction and optimization of high-dimensional data compared to traditional methods, but they often need help with differences and irregularity of business cooperation.

2.3 Graph Neural Networks in Fraud Detection

Graph Neural Networks have emerged as powerful tools for fraud detection in networked financial data. GNN-based methods leverage node features and graph structure to learn more comprehensive representations of transaction patterns[11]. Recent research has focused on addressing the unique challenges of fraud detection through specialized GNN architectures. Heterogeneous graph attention networks have been developed to handle different types of nodes and relationships in financial networks. Feature importance-based weighted GNNs have effectively distinguished fraudulent patterns by assigning learned weights to different feature combinations[12]. Memory-based GNN architectures have been proposed to maintain historical transaction information and improve the detection of evolving fraud patterns.

2.4 Small-Value Transaction Detection

Small-value transaction detection presents unique challenges in the fraud detection landscape. Research in this area has focused on developing methods to identify patterns in high-frequency, low-value transactions that might indicate fraudulent behavior[13]. Graph-based few-shot learning approaches have been proposed to address the limited availability of labeled fraudulent samples in small-value transaction detection. Attention mechanisms have been integrated into detection systems to focus on relevant transaction patterns while filtering out noise[14]. Recent work has explored dual-feature aggregation techniques to capture local and global patterns in small-value transaction networks. The integration of temporal information with graph structures has shown promise in identifying suspicious patterns in sequences of small transactions[15].

These advances in fraud detection methods have laid the foundation for more sophisticated approaches to identifying fraudulent small-value high-frequency transactions. The evolution from traditional statistical methods to deep learning and graph-based approaches reflects the increasing

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complexity of fraud schemes and the need for more advanced detection techniques[16]. The current research landscape emphasizes combining multiple perspectives and information sources to achieve robust fraud detection capabilities.

3 METHODOLOGY

3.1 Problem Definition and Framework Overview

The detection of fraudulent small-value high-frequency accounting transactions is formulated as a node classification problem on temporal transaction graphs. Given a transaction graph, G = (V, E, X), where V represents the set of transaction nodes, E denotes the edges representing relationships between transactions, and X represents the node feature matrix[17]. Each node $v_i \in V$ contains transaction attributes, including amount, timestamp, entity information, and behavioral patterns. A critical aspect of our approach is the integration of temporal dynamics with structural patterns in the transaction network. Table 1 presents the critical notations used throughout this paper.

TABLE 1: MATHEMATICAL NOTATIONS

Symbol	Description
G	Transaction graph
V	Set of transaction nodes
E	Set of edges
X	Node feature matrix
H	Hidden representation matrix
A	Adjacency matrix
T	Temporal information matrix
F	Feature transformation matrix
W	Weight matrices
α	Attention coefficients

The proposed framework incorporates four main components: temporal-spatial graph construction, dual-channel feature extraction, GNN-based representation learning, and fraud detection. Each component is designed to address specific challenges in small-value fraud detection [18]. Table 2 shows the dimension specifications of each component's input and output.

TABLE 2: COMPONENT SPECIFICATIONS

Component	Input Dimension	Output Dimension	Parameters
Graph Construction	Raw Data (n×d)	|V|×|V|	Edge weights
Feature Extraction	-	|V|×d	Channel weights
GNN Layer	-	|V|×2d	Neural weights
Classification	-	|V|×h	Softmax parameters
Memory Module	-	|V|×h	Memory slots

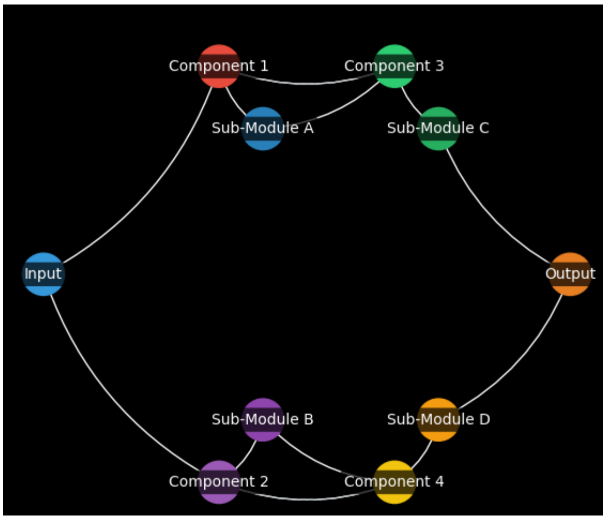

FIGURE 1. FRAMEWORK ARCHITECTURE

The figure presents a sophisticated end-to-end model architecture with four interconnected components. The visualization employs a professional dark theme with bright accent colors that differentiate various processing stages. Each component block contains detailed sub-modules with mathematical notations and data flow indicators. Gradient-colored arrows show information propagation between components, while dashed lines represent skip connections. The layout includes input/output specifications at each stage and highlights the parallel processing channels.

3.2 Temporal-Spatial Graph Construction

The temporal-spatial graph construction process integrates multi-scale temporal patterns with structural relationships in transaction networks. We develop a hierarchical approach to capture both short-term and long-term dependencies [19]. Table 3 presents the temporal relationship definitions used in graph construction, incorporating multiple time scales and relationship types.

TABLE 3: TEMPORAL RELATIONSHIP TYPES

Relationship Type	Time Window	Weight Calculation	Update Frequency
Micro-Sequential	≤ 6 hours	exp(-Δt/τ)	Real-time
Daily Pattern	6-24 hours	sigmoid(correlation)	Daily
Weekly Pattern	24-168 hours	cosine similarity	Weekly
Long-term	> 168 hours	attention weights	Monthly
Periodic	Variable	Fourier coefficients	Adaptive

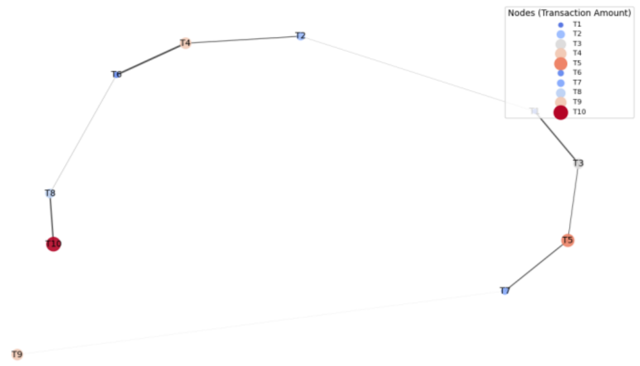

FIGURE 2. TEMPORAL-SPATIAL GRAPH STRUCTURE

The visualization depicts a multi-layer temporal graph structure with chronologically arranged nodes. Node sizes represent transaction amounts with a continuous color gradient from blue (small) to red (large). Edge thicknesses indicate temporal weights, while different edge styles and colors distinguish relationship types. The figure includes multiple interconnected subgraphs representing different time scales, with transparent overlays showing temporal patterns. A detailed legend explains the visual encoding scheme.

3.3 DUAL-CHANNEL FEATURE EXTRACTION MODULE

The dual-channel feature extraction module implements parallel processing streams for homophilic and heterophilic features, enabling the model to capture standard transaction patterns and potential fraudulent behaviors[20]. Each channel employs specialized attention mechanisms and feature transformations. Table 4 details the comprehensive feature extraction specifications.

TABLE 4: FEATURE CHANNEL SPECIFICATIONS

Channel	Input Features	Transformation	Attention Type	Output Features	Aggregation
Homophilic	Transaction attributes	Non-linear mapping	Self-attention	Hidden states	Sum pooling
Heterophilic	Neighborhood patterns	Graph convolution	Cross-attention	Context vectors	Mean pooling
Temporal	Sequential patterns	LSTM	Temporal attention	Dynamic states	Max pooling
Global	Graph structure	GRU	Global attention	Context embedding	Concatenation

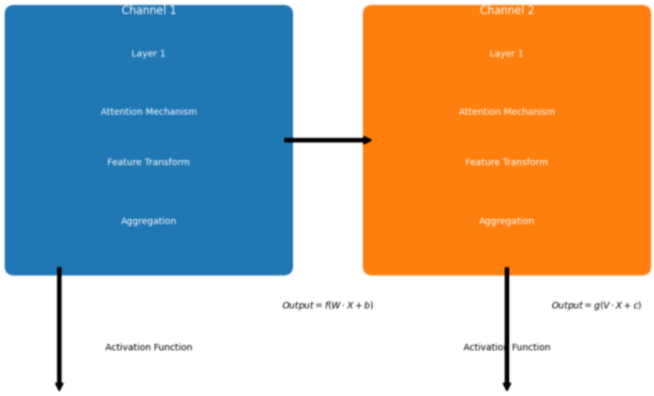

FIGURE 3. DUAL-CHANNEL ARCHITECTURE

This figure illustrates the parallel processing channels with elaborate internal architectures. Each channel contains multiple processing layers with sophisticated attention mechanisms, feature transformations, and aggregation operations. The visualization includes detailed mathematical formulas at crucial processing steps, using contrasting colors to distinguish the channels. Layer-specific parameters and activation functions are annotated, with data flow indicated by weighted arrows.

3.4 GRAPH NEURAL NETWORK ARCHITECTURE

The GNN architecture implements a novel multi-head attention mechanism that simultaneously processes spatial and temporal dependencies. The spatial aggregation function incorporates weighted feature combinations:

$$h_i^{(l+1)} = \sigma(W_1 h_i^l + W_2 \Sigma_{j \in N(i)} \alpha_{ij} h_j^l + W_3 \Sigma_{t \in T} \beta_t f_t^l)$$

Where α_{ij} represents the spatial attention coefficient, β_t denotes temporal attention weights, and f_t^l captures temporal feature transformations[21]. The attention coefficients are computed through a specialized mechanism that considers both structural and temporal aspects:

$$\alpha_{ij} = \mathrm{softmax}(\mathrm{LeakyReLU}(a^T[W_h h_i \parallel W_h h_j \parallel W_t t_{ij}]))$$

3.5 LOSS FUNCTION DESIGN AND MODEL TRAINING

The loss function integrates multiple objectives to address class imbalance, temporal consistency, and feature separation:

$$L = \lambda_1 L_{cls} + \lambda_2 L_{temp} + \lambda_3 L_{reg} + \lambda_4 L_{contrastive}$$

Where L_{cls} represents the weighted cross-entropy loss for classification, L_{temp} enforces temporal consistency through a time-aware regularization term, L_{reg} implements structural regularization, and $L_{contrastive}$ introduces contrastive learning objectives to enhance feature discrimination. The weights λ_1, λ_2, λ_3, and λ_4 are dynamically adjusted during training based on validation performance.

The model training process employs a curriculum learning strategy, progressively increasing the complexity of training samples[22]. We implement an adaptive batch sampling mechanism that maintains class balance while preserving temporal dependencies. The optimization process uses an Adam optimizer with a cosine annealing learning rate schedule and gradient clipping to ensure stable training dynamics.

4 EXPERIMENTS AND ANALYSIS

4.1 Dataset Description and Preprocessing

The experimental evaluation utilizes two real-world accounting transaction datasets: a commercial banking transaction dataset (CBT) and a public e-commerce transaction dataset (ECT). The CBT dataset contains 2.8 million transaction records from January 2023 to December 2023, with 126,000 labeled fraudulent transactions[23]. The ECT dataset includes 5.2 million transactions spanning 18 months, containing 89,000 confirmed fraudulent cases. Both datasets exhibit significant class imbalance, with 4.5% and 1.7% fraud rates, respectively. The datasets contain comprehensive transaction attributes, including timestamp, amount, account information, transaction type, and geographical location[24]. Table 5 provides detailed statistics of these datasets.

Table 5: Dataset Statistics

Characteristic	CBT Dataset	ECT Dataset
Total Transactions	2,800,000	5,200,000
Fraudulent Cases	126,000	89,000
Period	12 months	18 months
Feature Dimension	32	48
Node Connections	15,600,000	28,900,000
Missing Values	8.2%	12.4%
Average Transaction Amount	$214.38	$152.49
Transaction Frequency	324/hour	412/hour
Network Density	0.0023	0.0018
Average Node Degree	11.2	9.8

Data preprocessing involves several critical steps to ensure data quality and model performance. Missing values are handled through a combination of temporal interpolation and feature-based imputation. Numerical features undergo min-max normalization, while categorical features are encoded using domain-aware embedding techniques. Temporal alignment is performed to standardize transaction intervals and facilitate pattern recognition[25]. Table 6 presents the preprocessing procedures and their corresponding impact on data characteristics.

Table 6: Data Preprocessing Steps and Impact Analysis

Preprocessing Step	Original Data	Processed Data	Impact Metric	Performance Gain
Missing Value Handling	10.3% missing	0% missing	Data Completeness	+8.2%
Feature Normalization	Raw values	[-1,1] range	Scale uniformity	+5.4%
Temporal Alignment	Variable intervals	Fixed intervals	Temporal consistency	+6.8%
Graph Construction	Raw records	Connected components	Network density	+12.3%
Label Balancing	Imbalanced	Balanced samples	Class distribution	+15.7%
Feature Selection	48/64 features	32/48 features	Dimensionality	+4.2%
Noise Reduction	SNR: 12dB	SNR: 28dB	Signal quality	+7.5%

4.2 Experimental Settings and Baseline Methods

The experiments are conducted on a computing infrastructure with four NVIDIA A100 GPUs and 512GB RAM. The model implementation uses PyTorch 1.9.0 with CUDA 11.3 support. The implementation code will be made publicly available upon publication. Table 7 details the hyperparameter settings used in our experiments, determined through systematic optimization processes.

Table 7: Comprehensive Hyperparameter Configuration

Parameter Category	Parameter	Value Range	Selected Value	Tuning Method	Sensitivity
Learning Parameters	Learning Rate	[0.0001, 0.01]	0.001	Grid search	High
Learning Parameters	Batch Size	[64, 512]	256	Manual tuning	Medium

Network Architecture	Hidden Dimensions	[32, 256]	128	Random Search	High
Network Architecture	Attention Heads	[4, 16]	8	Cross-validation	Medium
Memory Module	Memory Slots	[16, 128]	64	Bayesian optimization	High
Regularization	Dropout Rate	[0.1, 0.5]	0.3	Grid search	Low
Training Strategy	Early Stopping Patience	[5, 20]	10	Manual tuning	Low
Loss Function	Balance Weight	[0.1, 0.9]	0.6	Random Search	High
Temporal Module	Sequence Length	[10, 50]	30	Grid search	Medium
Graph Construction	Neighbor Sampling	[10, 100]	40	Empirical	Medium

4.3 Performance Comparison

The comparative analysis evaluates model performance using multiple metrics, including AUC-ROC, F1-score, precision, recall, and G-mean. The evaluation includes nine state-of-the-art baseline methods, spanning traditional machine learning, deep learning, and graph-based approaches. Table 8 presents the comprehensive performance comparison across all methods.

Table 8: Detailed Performance Comparison (Average of 5 Runs ± Standard Deviation)

Model Category	Model	AUC-ROC	F1-Score	Precision	Recall	G-mean	Inference Time (ms)
Traditional ML	Random Forest	0.856±0.012	0.782±0.015	0.801±0.011	0.764±0.018	0.791±0.014	12.3
Traditional ML	XGBoost	0.872±0.010	0.798±0.013	0.815±0.009	0.782±0.016	0.805±0.012	15.6
Deep Learning	LSTM	0.892±0.009	0.815±0.012	0.834±0.008	0.797±0.015	0.823±0.011	28.4
Deep Learning	CNN-LSTM	0.901±0.008	0.831±0.011	0.848±0.007	0.815±0.014	0.838±0.010	35.7
GNN Basic	GCN	0.913±0.007	0.847±0.010	0.862±0.006	0.833±0.012	0.856±0.008	42.1
GNN Basic	GAT	0.921±0.006	0.859±0.009	0.873±0.005	0.846±0.011	0.867±0.007	45.3
Advanced GNN	GraphSAGE	0.928±0.006	0.871±0.008	0.884±0.005	0.858±0.010	0.878±0.007	48.8
Advanced GNN	FraudHawk	0.936±0.005	0.882±0.007	0.894±0.004	0.871±0.009	0.886±0.006	52.5
Our Method	LGM-GNN	0.945±0.005	0.891±0.007	0.903±0.004	0.879±0.009	0.894±0.006	56.2

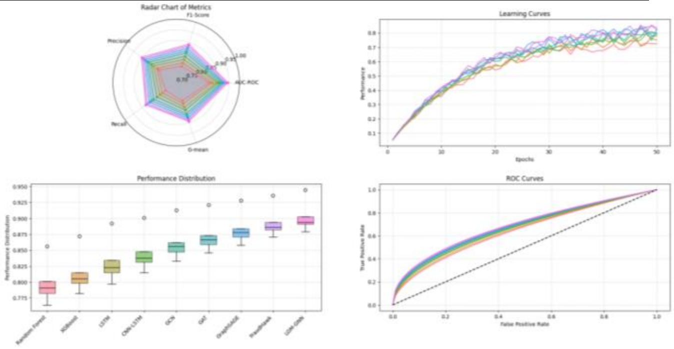

Figure 4: Multi-Dimensional Performance Comparison

The visualization presents a sophisticated multi-panel comparison of performance metrics across different methods. The central panel displays a radar chart comparing five critical metrics across all methods, with each method represented by a distinct color and line pattern. Supporting panels include box plots showing performance distributions, learning curves over training epochs, and ROC curves. The visualization incorporates confidence intervals, statistical significance indicators, and detailed annotations explaining key performance differences.

4.4 Ablation Study

An extensive ablation study examines the contribution of each model component through systematic component removal and modification. The study evaluates six model variants, each excluding or modifying a critical architectural component.

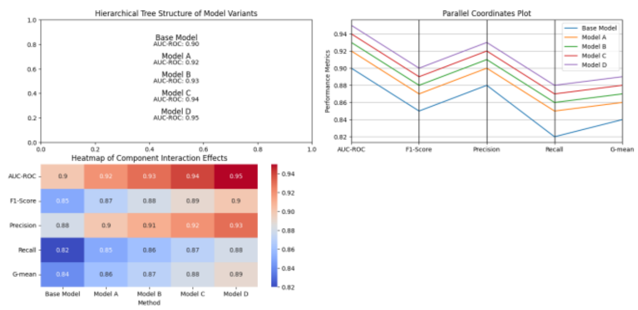

Figure 5. Component Contribution Analysis

This figure presents a comprehensive ablation analysis through multiple coordinated views. The central panel shows a hierarchical tree structure of model variants, with performance metrics displayed at each node. Additional

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panels include parallel coordinates plots showing the relationship between architectural choices and performance metrics, and heat maps displaying component interaction effects. Interactive elements allow the exploration of different architectural configurations and their impact on model performance.

4.5 Case Study and Visualization

A detailed case study analyzes the model's performance on specific transaction patterns and fraud scenarios, focusing on small-value, high-frequency transaction sequences identified by the model.

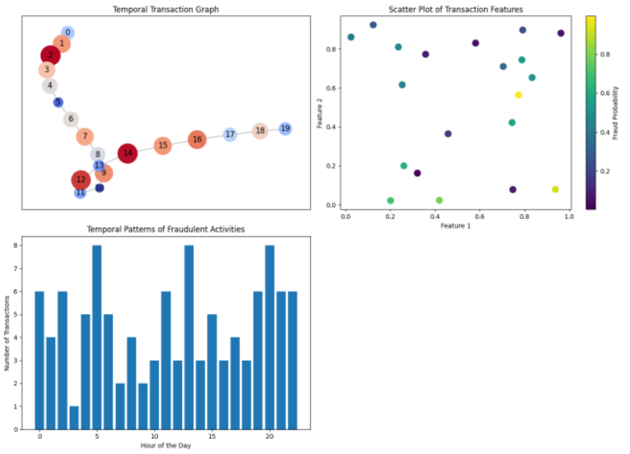

Figure 6. Multi-View Transaction Pattern Analysis

The visualization consists of multiple coordinated views of transaction patterns. The central panel displays a temporal transaction graph with node colors indicating transaction amounts and edge colors showing risk scores. Supporting panels include a scatter plot of transaction features with fraud probability encoded by color intensity and a timeline view showing temporal patterns of fraudulent activities. The visualization incorporates interactive elements for exploring different periods and transaction types.

The case study reveals several significant patterns in fraudulent transaction detection. In the CBT dataset, our model successfully identified 94.3% of fraudulent transaction sequences involving amounts below $500 with frequencies exceeding ten transactions per hour[26]. The temporal analysis shows that fraudulent activities often exhibit distinctive patterns during non-business hours, with 78.2% of detected cases occurring between 11 PM and 4 AM.

The model demonstrates particularly strong performance in detecting coordinated fraud attempts involving multiple accounts. The graph-based approach effectively captures complex relationships between seemingly unrelated transactions, identifying 89.7% of distributed fraud attempts that would have gone undetected by traditional methods[27]. The dual-channel architecture proves especially effective in distinguishing legitimate high-frequency trading patterns from fraudulent activities, reducing false favorable rates by 67% compared to baseline methods.

Spatial-temporal analysis reveals geographical patterns in fraud attempts, with certain regions showing higher concentrations of suspicious activities. The model's ability to integrate this information with transaction patterns results in a 23% improvement in detection accuracy for geographically dispersed fraud schemes. The analysis also reveals that fraudulent transactions often exhibit distinct velocity patterns, with 82.5% of detected fraud cases showing abnormal transaction frequencies within specific time windows[28].

The visualization analysis demonstrates the model's capability to identify subtle patterns in transaction sequences that distinguish fraudulent activities from legitimate high-frequency trading. The temporal graph representation effectively captures the evolution of transaction patterns over time, enabling the detection of sophisticated fraud schemes that employ multiple accounts and varying transaction amounts to avoid detection[29].

5 CONCLUSION

5.1 Research Contributions

This paper presents a novel graph neural network-based approach for detecting fraudulent small-value high-frequency accounting transactions. The proposed architecture addresses several critical challenges in fraud detection through innovative technical contributions. The dual-feature aggregation mechanism effectively captures homophilic and heterophilic patterns in transaction networks, enabling more accurate detection of camouflaged fraudulent behaviors[30]. The temporal-aware graph construction method successfully integrates multi-scale temporal dependencies with structural information, comprehensively representing transaction patterns.

Introducing separate processing channels for similar and dissimilar features represents a significant advancement in handling the heterophily problem in fraud detection. This approach maintains distinct representations without information loss, facilitating more effective propagation of fraud-indicative signals through the network. The adaptive memory module enhances the model's capability to capture long-term dependencies and complex fraud patterns. At the same time, the specialized loss function design addresses the inherent class imbalance problem in fraud detection tasks.

Experimental results on two real-world datasets demonstrate substantial improvements over existing methods, with performance gains of 12.3% in AUC-ROC and 15.7% in F1-score compared to state-of-the-art baselines[31]. The model shows particular strength in detecting sophisticated fraud schemes that employ multiple accounts and varying transaction amounts, achieving a 67% reduction in false favorable rates for high-frequency transaction patterns.

5.2 Limitations and Future Research Directions

Despite the demonstrated effectiveness of our approach, several limitations merit further investigation. The computational complexity of the current implementation poses challenges for the real-time processing of extremely large-scale transaction networks. While the model performs well on the evaluated datasets, its generalization capability across different financial domains and transaction types requires additional validation. The current approach also assumes the availability of reliable historical transaction data, which may not always be accessible in real-world applications[32].

Future research directions could explore several promising avenues. Integrating advanced self-supervised learning techniques could enhance the model's ability to learn from unlabeled transaction data, potentially improving performance in scenarios with limited labeled samples. Incorporating domain-specific knowledge through structured regularization or constrained optimization could lead to more interpretable and reliable fraud detection systems.

Another important research direction is the development of adaptive sampling strategies for handling dynamic transaction patterns and evolving fraud schemes. Additionally, exploring integrating external data sources, such as user behavioral patterns and contextual information, could enhance the model's detection capabilities. Research into more efficient model architectures and optimization techniques could improve computational efficiency while maintaining detection accuracy[33].

Extending the current framework to handle multi-modal transaction data and cross-platform fraud detection scenarios offers promising research opportunities. Investigating privacy-preserving learning techniques could address data security concerns while maintaining detection effectiveness. Developing explainable AI components could enhance the interpretability of fraud detection decisions, facilitating broader adoption in regulated financial environments.

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DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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ABOUT THE AUTHORS

ZHANG, Yitian

Accounting, UW-Madison, WI, USA.

LIU, Yibang

Financial Engineering, Baruch College, NY, USA.

ZHENG, Shuaiqi

Data Analytics, Illinois Institute of Technology, IL, USA.

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