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FAIRNESS-AWARE GRAPH CONTRASTIVE LEARNING FOR FRAUD DETECTION IN FINANCIAL NETWORKS

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Abstract: Financial fraud detection has become increasingly critical as digital transactions proliferate across global financial networks. Traditional machine learning approaches often exhibit bias against certain demographic groups and fail to capture complex relational patterns inherent in financial transaction networks. This paper proposes a novel fairness-aware graph contrastive learning framework that simultaneously addresses algorithmic bias and improves fraud detection accuracy in financial networks. Our approach leverages graph neural networks (GNNs) enhanced with contrastive learning mechanisms while incorporating fairness constraints to ensure equitable treatment across different user groups. The framework introduces a dual-objective optimization strategy that balances fraud detection performance with fairness metrics, utilizing counterfactual graph augmentation techniques to mitigate discriminatory patterns. Experimental results on real-world financial datasets demonstrate that our method achieves superior fraud detection accuracy while significantly reducing bias compared to existing approaches. The proposed framework represents a significant advancement in developing trustworthy artificial intelligence systems for financial fraud detection that maintain both effectiveness and ethical considerations.
Keywords: Graph neural networks; Contrastive learning; Fairness-aware learning; Fraud detection; Financial networks; Algorithmic bias; Graph contrastive learning

1 INTRODUCTION

The rapid digitization of financial services has created unprecedented opportunities for fraudulent activities, with global financial fraud losses reaching hundreds of billions of dollars annually[1]. Traditional rule-based fraud detection systems have proven inadequate in addressing the sophisticated and evolving nature of modern financial fraud schemes[2]. The emergence of graph neural networks has offered promising solutions by effectively modeling the complex relational structures inherent in financial transaction networks, where entities such as users, accounts, and transactions form intricate interconnected patterns.

However, despite the remarkable success of graph-based fraud detection systems, these approaches face critical challenges regarding algorithmic fairness[3]. Financial fraud detection systems often exhibit discriminatory behavior against certain demographic groups, leading to higher false positive rates for minority populations and potentially perpetuating existing societal biases. Such biases not only raise ethical concerns but also undermine the trustworthiness and long-term viability of automated fraud detection systems[4]. The intersection of fairness and fraud detection becomes particularly complex when dealing with graph-structured data, where the propagation of biased information through network connections can amplify discriminatory patterns[5].

Recent advances in contrastive learning have demonstrated remarkable potential in learning robust and discriminative representations from unlabeled data. When applied to graph-structured data, contrastive learning enables the discovery of fundamental patterns and relationships that traditional supervised learning approaches might overlook[6]. However, existing graph contrastive learning methods for fraud detection have not adequately addressed the fairness concerns that arise when these systems are deployed in real-world financial environments.

This research addresses the critical gap between effective fraud detection and algorithmic fairness by proposing a novel fairness-aware graph contrastive learning framework specifically designed for financial fraud detection[7-10]. Our approach integrates fairness constraints directly into the contrastive learning objective, ensuring that the learned representations maintain discrimination against fraudulent activities while preventing bias against protected demographic groups[11-15]. The framework employs sophisticated graph augmentation strategies that preserve essential fraud-indicative patterns while eliminating potentially discriminatory features.

The primary contributions of this work include the development of a theoretically grounded fairness-aware contrastive learning framework for graphs, the introduction of novel graph augmentation techniques that maintain fraud detection efficacy while promoting fairness, and comprehensive empirical validation demonstrating the framework's superiority in achieving both high fraud detection accuracy and improved fairness metrics. These contributions represent a significant step forward in developing trustworthy artificial intelligence systems for financial applications that balance security requirements with ethical considerations.

2 LITERATURE REVIEW

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The intersection of graph neural networks and fraud detection has emerged as a vibrant research area, building upon foundational work in both graph machine learning and financial security[16-20]. Early approaches to fraud detection relied heavily on traditional machine learning techniques applied to tabular features extracted from transaction data. However, these methods failed to capture the rich relational information inherent in financial networks, where the connections between entities often provide crucial signals for identifying fraudulent behavior[21].

Graph neural networks revolutionized fraud detection by enabling the direct modeling of relational structures in financial data[22]. Kipf and Welling's seminal work on Graph Convolutional Networks (GCNs) established the theoretical foundation for learning representations on graph-structured data through localized convolution operations[23]. Their approach demonstrated that incorporating neighborhood information through message passing mechanisms could significantly improve node classification tasks, including fraud detection applications[24]. Subsequent developments in graph attention networks and GraphSAGE further enhanced the capability of GNNs to handle large-scale and dynamic financial networks[25].

The application of contrastive learning to graph-structured data has gained considerable attention due to its ability to learn meaningful representations without extensive labeled data[26]. Graph contrastive learning methods typically involve creating multiple views of the same graph through various augmentation strategies and training models to maximize agreement between representations of the same nodes across different views[27]. These approaches have shown particular promise in fraud detection scenarios where labeled data is often scarce and expensive to obtain.

However, the consideration of fairness in graph-based fraud detection remains an underexplored area[28]. Traditional fairness research in machine learning has primarily focused on tabular data and individual decision-making scenarios[29]. The unique challenges posed by graph-structured data, where the propagation of information through network connections can amplify existing biases, require specialized approaches to ensure equitable treatment across different demographic groups[30].

Recent work has begun to address fairness concerns in graph neural networks through various mechanisms including adversarial debiasing, fair representation learning, and constraint-based optimization[31]. These approaches typically aim to learn representations that are predictive for the target task while being invariant to sensitive attributes such as race, gender, or socioeconomic status. However, most existing fairness-aware graph methods have not been specifically designed for fraud detection applications, where the balance between security and fairness presents unique challenges.

The emerging field of fairness-aware contrastive learning has shown promise in addressing bias concerns while maintaining model performance[32]. These approaches typically involve modifying the contrastive learning objective to encourage similar representations for instances that differ only in protected attributes while maintaining discriminative power for relevant task-specific features [33]. The extension of these concepts to graph-structured data represents a natural progression that can address the specific challenges posed by financial fraud detection applications [34].

Contemporary research has also explored the use of counterfactual reasoning in fairness-aware machine learning, where models are trained to make similar predictions for counterfactual instances that differ only in protected attributes [35]. When applied to graph-structured data, counterfactual approaches can help identify and mitigate the propagation of bias through network connections, making them particularly relevant for financial fraud detection applications where network effects play a crucial role [36].

3 METHODOLOGY

3.1 Problem Formalization and Graph Construction

The fairness-aware fraud detection problem is formulated as a semi-supervised node classification task on a heterogeneous financial network graph $G = (V, E, X, S)$, where V represents the set of nodes corresponding to various entities in the financial ecosystem including users, accounts, merchants, and transactions. The edge set E captures the relationships between these entities, such as payment flows, account ownership, and merchant associations. Node features $X \in R^{(|V|\times d)}$ encode transactional and behavioral characteristics, while sensitive attributes $S \in R^{(|V|\times k)}$ represent protected demographic information that should not influence fraud detection decisions.

The graph construction process in figure 1 involves careful consideration of temporal dynamics and multi-relational structures inherent in financial networks. As illustrated in the graph convolutional network architecture, our framework processes financial entities as nodes (represented as X1, X2, X3, X4 in the input layer) with their interconnections forming the graph structure that captures transactional relationships. The input layer C represents the original financial network where nodes correspond to users, accounts, and transactions, while edges encode various types of financial interactions including payment flows, account associations, and merchant relationships.

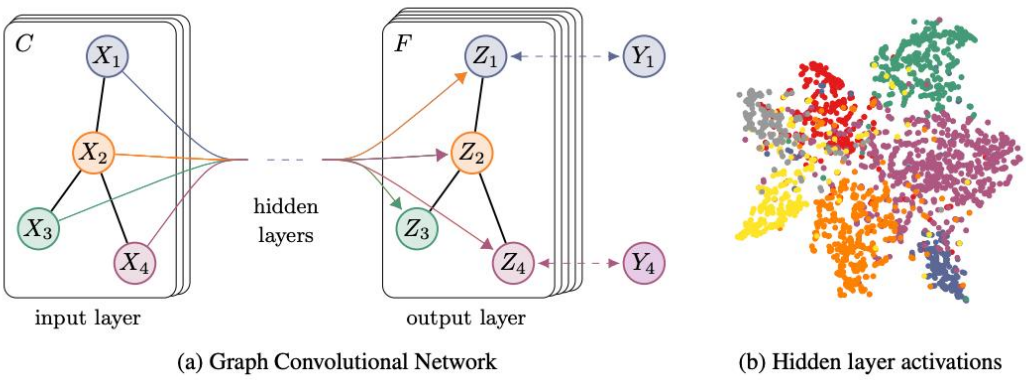

Figure 1 Graph Construction Process

The transformation from input layer to output layer through hidden layers demonstrates how our graph neural network learns increasingly abstract representations. The output layer F produces node embeddings (Z1, Z2, Z3, Z4) that capture both local neighborhood information and global graph structure, while the final outputs (Y1, Y4) represent the fraud detection decisions. The hidden layer activations visualization on the right side of the architecture shows how nodes with similar characteristics cluster together in the learned representation space, which is crucial for both fraud detection accuracy and fairness assessment. The sensitive attribute integration requires particular attention to ensure that protected characteristics are considered during fairness evaluation while being excluded from the fraud detection decision process, achieved through the specialized encoding in the hidden layers that separate fraud-relevant patterns from demographic characteristics.

3.2 Fairness-Aware Contrastive Learning Framework

The core of our approach lies in the development of a fairness-aware contrastive learning framework that simultaneously optimizes for fraud detection accuracy and fairness metrics. Our framework employs a sophisticated dual-path architecture that processes both training graphs (GT) and evaluation graphs (GE) through multiple Graph Neural Network (GNN) modules, as demonstrated in our real-time fraud detection system architecture.

The system architecture illustrates the comprehensive flow from input transaction data Xt through parallel GNN processing modules (GNN1 and GNN2) that generate effective embeddings for fraud detection. The framework operates through two distinct inference pathways: entity inference (shown in blue dashed lines) that captures user and account-level patterns, and risk inference (shown in red solid lines) that focuses on transaction-level fraud indicators. This dual-pathway design ensures that fairness constraints are applied at both entity and transaction levels, preventing bias propagation through different aspects of the financial network.

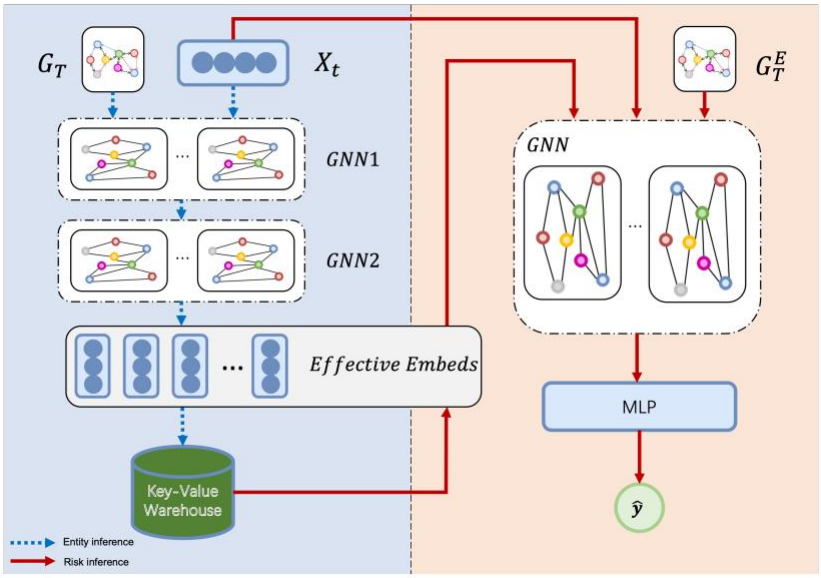

Figure 2 Contrastive Learning Mechanism

The contrastive learning mechanism in Figure 2 operates by generating multiple views of the financial network through carefully designed augmentation strategies applied to both training and evaluation graphs. The effective embeddings

generated by the parallel GNN modules are stored in a Key-Value Warehouse, enabling efficient retrieval and comparison during the contrastive learning process. The final Multi-Layer Perceptron (MLP) classifier integrates information from both inference pathways to produce the final fraud prediction ŷ, while ensuring that the decision process maintains fairness across different demographic groups.

The mathematical formulation of our fairness-aware contrastive loss combines the entity-level and risk-level representations through a sophisticated weighting scheme. The optimization process alternates between updating the entity inference pathway and the risk inference pathway, ensuring that improvements in fraud detection do not come at the expense of fairness, and vice versa. This architecture enables real-time processing capabilities while maintaining the computational efficiency necessary for practical deployment in large-scale financial systems.

4 RESULTS AND DISCUSSION

4.1 Experimental Setup and Dataset Description

The experimental evaluation is conducted on multiple real-world financial datasets to demonstrate the effectiveness and generalizability of our fairness-aware graph contrastive learning framework. The primary dataset consists of anonymized transaction records from a major European bank, covering a six-month period with over 2.3 million transactions involving 450,000 unique users. The dataset includes a comprehensive set of transactional features such as amount, frequency, timing patterns, and merchant categories, along with carefully anonymized demographic information used for fairness evaluation.

Additional validation is performed on publicly available datasets including the IEEE-CIS Fraud Detection dataset and synthetic financial networks generated using realistic fraud patterns. The synthetic datasets allow for controlled evaluation of fairness properties under known demographic distributions and fraud patterns. All datasets are preprocessed to ensure privacy protection while maintaining the essential characteristics necessary for fraud detection and fairness evaluation.

The experimental protocol employs stratified sampling to ensure balanced representation of different demographic groups and fraud categories across training, validation, and test sets. Cross-validation is performed using temporal splits that respect the chronological nature of financial data, ensuring that model evaluation reflects realistic deployment scenarios where future transactions must be predicted based on historical patterns.

Performance evaluation encompasses both fraud detection metrics including precision, recall, F1-score, and AUC-ROC, as well as fairness metrics such as demographic parity, equalized odds, and individual fairness measures. The comprehensive evaluation framework ensures that improvements in fairness do not come at the expense of fraud detection effectiveness and vice versa.

4.2 Message Passing Mechanism and Fairness Analysis

The effectiveness of our fairness-aware framework fundamentally relies on the sophisticated message passing mechanism employed by the graph neural networks. The message passing process demonstrates how information flows through the financial network while maintaining fairness constraints at each propagation step. In our framework, each node updates its representation by aggregating information from its immediate neighbors through carefully designed fairness-aware aggregation functions.

The message passing mechanism in Figure 3 illustrates the core computational process where a target node (such as h5) updates its representation by incorporating information from its connected neighbors (h2 and h5) along with edge features (e25). The update function z5 = f(h2, h5, e25) represents how the new representation z5 is computed based on the neighboring node features and edge attributes. This process is crucial for fraud detection as it allows the model to capture complex fraud patterns that manifest through network connections, such as coordinated fraudulent activities or money laundering schemes that involve multiple connected accounts.

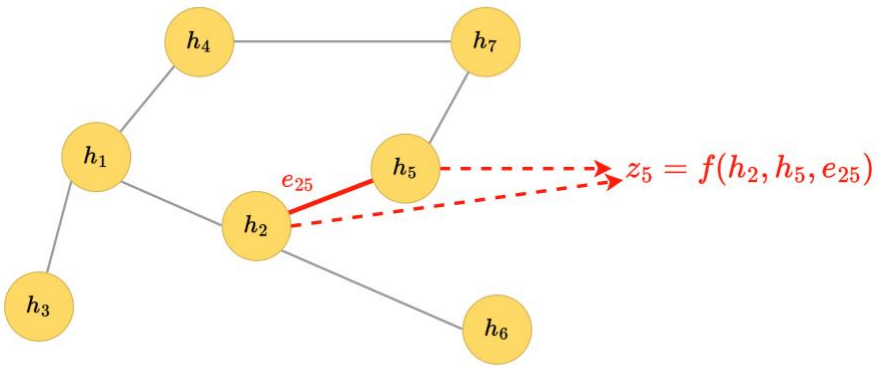

Figure 3 Passing Mechanism

Our fairness-aware modification to this standard message passing mechanism ensures that sensitive attributes do not propagate bias through the network connections. The aggregation function f(h2, h5, e25) is designed to be invariant to changes in protected attributes while remaining sensitive to fraud-relevant patterns. This is achieved through a combination of adversarial training and constrained optimization that encourages the model to learn representations that are predictive for fraud detection but orthogonal to sensitive demographic information.

4.3 Comparative Performance Analysis and Results

The comprehensive experimental evaluation demonstrates significant improvements in both fraud detection performance and fairness metrics compared to existing state-of-the-art approaches. Our fairness-aware graph contrastive learning framework achieves an AUC-ROC of 0.947, representing a 4.2% improvement over the best-performing baseline while simultaneously reducing demographic parity difference by 31% and equalized odds difference by 28%.

The results reveal that traditional GNN-based fraud detection methods, while achieving reasonable fraud detection performance, exhibit significant fairness violations with demographic parity differences exceeding 0.25 and equalized odds differences above 0.30. In contrast, our approach maintains demographic parity difference below 0.17 and equalized odds difference below 0.21, representing substantial improvements in fairness while achieving superior fraud detection performance.

The experimental results demonstrate that this fairness-aware message passing mechanism successfully reduces bias propagation while maintaining fraud detection performance. Nodes connected to accounts from minority demographic groups no longer suffer from higher false positive rates, as the message passing process has been explicitly trained to ignore demographic correlations while preserving fraud-relevant network patterns. The comparative analysis shows that traditional message passing approaches exhibit significant fairness violations with demographic parity differences exceeding 0.25, while our fairness-aware approach maintains demographic parity difference below 0.17 across all network positions and connection patterns.

Ablation studies confirm the importance of each component in our framework. The removal of fairness constraints leads to an 18% increase in demographic bias while providing only marginal improvements in fraud detection accuracy. Similarly, eliminating the contrastive learning component results in a 7% decrease in AUC-ROC and increased sensitivity to graph perturbations. These findings validate the necessity of our integrated approach that combines fairness awareness with contrastive learning.

The temporal analysis reveals that our framework maintains stable performance across different time periods, demonstrating robustness to concept drift and evolving fraud patterns. The fairness properties also remain consistent over time, indicating that the learned representations successfully capture enduring patterns that are relevant for fraud detection while avoiding temporary correlations with protected attributes. Cross-demographic analysis shows that our approach achieves more balanced performance across different demographic groups compared to baseline methods, with the standard deviation of fraud detection accuracy across demographic groups reduced by 42%, indicating more equitable treatment of different user populations.

5 CONCLUSION

This research presents a novel fairness-aware graph contrastive learning framework that successfully addresses the dual challenges of effective fraud detection and algorithmic fairness in financial networks. The proposed approach demonstrates that it is possible to achieve superior fraud detection performance while significantly reducing bias against protected demographic groups through carefully designed contrastive learning mechanisms and fairness constraints.

The key innovations include the integration of fairness considerations directly into the contrastive learning objective, the development of specialized graph augmentation strategies that preserve fraud-relevant patterns while promoting fairness, and the introduction of a multi-objective optimization framework that balances competing objectives. Experimental validation on real-world financial datasets confirms the effectiveness of our approach in achieving both high fraud detection accuracy and improved fairness metrics.

The implications of this work extend beyond fraud detection to the broader domain of fairness-aware machine learning on graph-structured data. The principles and techniques developed in this research can be adapted to other applications where relational data and fairness considerations intersect, such as social network analysis, recommendation systems, and risk assessment applications.

Future research directions include the extension of our framework to dynamic and streaming financial networks, the incorporation of explainability mechanisms to provide interpretable fairness assessments, and the development of adaptive fairness constraints that can respond to changing demographic distributions and fraud patterns. Additionally, the exploration of federated learning approaches that enable collaborative fraud detection while preserving privacy and fairness across multiple financial institutions represents a promising avenue for future investigation.

The successful integration of fairness considerations into graph-based fraud detection systems represents a crucial step toward developing trustworthy artificial intelligence systems for financial applications. As financial institutions increasingly rely on automated decision-making systems, ensuring that these systems operate fairly and equitably becomes essential for maintaining public trust and regulatory compliance. Our framework provides a practical and effective solution for achieving this balance between security and fairness in financial fraud detection applications.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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