10.48047/jocaaa.2020.28.04.06

Graph-ID: Inductive Graph Neural Networks for High-Fidelity Relational Anomaly Detection in Digital Interaction Networks

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Abstract

Detecting anomalous behavior in digital interaction networks is increasingly challenging due to the relational complexity and temporal evolution of modern digital ecosystems. Traditional anomaly detection methods often fail to generalize to unseen nodes or evolving network structures. This research introduces Graph-ID, an inductive graph neural network (GNN) framework for relational behavioral anomaly detection in dynamic digital interaction networks. By leveraging node-level embeddings and neighborhood aggregation, the framework captures both local and higher-order relational patterns across heterogeneous user interactions. The model employs a multi-relational attention mechanism to assign adaptive importance to distinct behavioral edges, enabling detection of subtle deviations indicative of fraudulent or synthetic identities. Temporal edge encoding captures both immediate anomalies and long-term behavioral drifts. Empirical evaluation on large-scale multi-modal interaction datasets demonstrates that Graph-ID achieves an F1-score of 0.89, precision of 0.91, recall of 0.87, and AUROC of 0.93, representing 25–30% improvements over baseline graph embedding and unsupervised anomaly detection methods. Notably, the inductive design allows robust generalization to previously unseen nodes and evolving network topologies. These results establish inductive GNNs as a scalable and practical methodology for high-fidelity anomaly detection, providing a foundational tool for operational security and fraud prevention in complex digital ecosystems.

Keywords: Graph neural networks, Relational anomaly detection, Digital interaction networks, Inductive learning, Behavioral analysis, Network security, Detection accuracy.

1. INTRODUCTION

Digital interaction networks have increased in size and complexity as a result of the growing dependence on online platforms for communication, trade, and information sharing [1]. Digital interaction networks are complex in that they consist of heterogeneous elements and interactions, which create complex relational structures that represent user behavior, organizational processes, and digital interactions [2]. Anomalies in the behavior of such networks are indicative of possible fraud, cyber threats, and misuse of the system, which makes their detection essential for security, trust, and stability [3]. The interconnected nature of nodes and edges in networks means that anomalies are not isolated events but occur as a result of unusual patterns of interaction or relational anomalies that deviate from normal network behavior. Statistical and graph-based methods have traditionally been used to identify these anomalies, such as centrality metrics, clustering, and probabilistic models, which offer a fundamental understanding of patterns, anomalies, and structural irregularities in large-scale networks [4].

Recent studies underscore the need for modeling not only individual behaviors but also the relationships and dependencies between entities. The use of structured features to represent nodes and edges enables the description of normal and anomalous patterns in various dimensions [5]. Network embedding, spectral graph methods, and message passing models enable the measurement of relational behaviors and comparison with normal expectations [6]. Furthermore, the dynamic nature of digital networks demands models that can detect evolving patterns, as static models may not be able to identify new

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anomalies. Inferential and descriptive statistical analysis is critical for understanding variability, correlation, and significance of observed anomalies, while computational frameworks are necessary for large and high-dimensional interaction data [7]. These advances collectively indicate the need for advanced models that can identify complex relational anomalies while being able to adapt to growth, diversity, and dynamics of digital interaction networks [8].

The present work aims at designing an inductive graph-based framework for relational behavioral anomaly detection in digital interaction networks. The objective is to detect unusual interaction patterns among entities that may point to fraud, abuse, or security risks in large-scale dynamic digital networks. The work is motivated by the growing complexity and volume of digital interactions that make traditional anomaly detection techniques less effective and require the development of generalized models that can handle unseen nodes and interactions. The objectives of the work include designing a scalable inductive graph neural network that can learn relational embeddings, designing anomaly scoring functions based on neighborhood deviations, and evaluating performance on multiple datasets. The work will make a significant contribution to the design of a relational anomaly detection framework that combines both statistical and structural knowledge. The paper is structured to provide a systematic overview of background, related work, methodology, experiments, results, discussion, and conclusions.

2. LITERATURE SURVEY

The fast progress of graph neural networks (GNNs) and graph-based anomaly detection techniques indicates an increasing awareness of the fact that the relational structure in network data encodes complex behavioral patterns, which cannot be well modeled by traditional feature-based anomaly detection algorithms. There has been a growing interest in using graph structures to represent interactions between entities and designing neural networks to learn embeddings that encode structural and attribute information for anomaly detection. The study indicates substantial progress in heterogeneous and attributed graph modeling, attention mechanisms for modeling relational subtleties, and dedicated architectures for fraud, malicious account identification, and cash-out user fraud, which rely on intricate interaction patterns. These studies together emphasize the importance of relational learning, graph aggregation techniques, and attention mechanisms to identify anomalous patterns from intricate digital interaction graphs [9].

A. Chaudhary et al. [10] introduced a heterogeneous graph neural network (GEM) for identifying malicious accounts in a mobile cashless payment system, highlighting the significance of modeling relationships between different types of entities. In this research, a heterogeneous graph structure was designed to model accounts and their corresponding device types, and an attention mechanism was employed to learn node embeddings that emphasized significant relationship patterns. Through aggregating graph channel information of multi-typed graphs, the method showed better detection results than competitive baselines, confirming the effectiveness of graph learning in modeling relational anomalies. This research highlights the difficulty of jointly modeling structural and attribute information to identify minute fraudulent patterns hidden in network interactions.

Y. Chu et al. [11] proposed a hierarchical attention mechanism model for the detection of cash-out users on an attributed heterogeneous information network (AHIN), particularly emphasizing financial fraud detection, in which the patterns of interaction and attribute features are intricately entwined. The paper exemplified the various object types and their interaction relationships through meta-paths to demonstrate the diverse relational structures through the application of attention to represent user preference for particular relationships and attributes. This paper emphasizes the significance of incorporating both structural path and feature interaction in the process of distinguishing behavioral anomalies in financial networks through hierarchical relational representations as opposed to feature-based approaches.

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The research surveys and compendia (e.g., the GNN anomaly detection overview) conducted by K. Ding et al. [12] traced the development of graph neural network methods for anomaly detection problems, such as malicious account detection and spam detection, using graph convolutional networks and attention models. The study systematically classified various GNN-based methods according to the types of graphs (static vs. dynamic) and the types of anomalies (node, edge, and subgraph), emphasizing the importance of relational learning through embedding methods such as GCN and attention. These studies provided valuable information on how architectural design affects detection accuracy and informed the development of relational anomaly detection.

X. Li et al.'s [13] HACUD model represented an improvement in relational anomaly detection by integrating hierarchical attention mechanisms with heterogeneous networks to better understand the significance of structural interaction patterns and attribute significance in user, merchant, and transaction relationships. This study showed that the consideration of relational details through meta-paths improves the quality of detection, particularly in interaction sequences that are normally ignored by traditional anomaly detection methods. The use of meta-path-based neighbor exploration in their study shows the significance of multi-aspect paths in identifying deviated behavior in network settings.

Vassilis N. Ioannidis et al. [14] proposed GraphSAC, a node anomaly detection method that utilizes graph sampling and consensus to reduce the effect of noisy data on learned distributions, thus facilitating the detection of anomalies in graphs at a large scale without relying on global connectivity. Although not a GNN per se, this graph-conscious anomaly detection model proposed important concepts related to relational behavior detection, including randomized subgraph sampling to detect anomalous patterns over structural variations, thus providing a different perspective complementary to the neural approach centered on neighborhood aggregation.

F. Corò et al. [15] introduced AddGraph, an anomaly detection framework specifically designed for dynamic graph environments, where the evolution of interaction over time is of prime importance. By integrating temporal graph convolution mechanisms based on attention mechanisms, the framework was able to learn both relational and temporal features simultaneously, which helped in identifying anomalous edges and temporal patterns. This dynamic learning highlights the importance of learning both structural and temporal relational behaviors in digital interaction networks, particularly in environments where anomalies can be identified by the evolution of actions over time.

Table 1: Summary of Network Anomaly Detection Approaches

Study	Methods	Key Findings
[16]	Dynamic network embedding using deep autoencoder and clique embedding; learns low-dim vectors for evolving graphs.	Proposed an efficient dynamic network embedding method that updates representations and detects anomalies in real time; improved detection capability for streaming and evolving structures.
[17]	Graph dense-block detection in bipartite graphs with camouflage-resistant anomaly metrics.	Developed a camouflage-resistant algorithm for detecting fraudulent subgraphs in large real networks; demonstrated improved identification of fraudsters hidden within normal structures.
[18]	Joint modeling approach for anomaly detection on attributed networks (embedding + model integration).	Introduced a unified approach combining structure and attribute information, yielding better anomaly detection performance on attributed network datasets.
[19]	Accelerated local anomaly detection framework via resolving attributed networks.	Provided an efficient method to spot local abnormal structures in attributed networks using scalable optimization techniques, enhancing detection precision.
[20]	Residual analysis for anomaly detection in attributed networks.	Employed graph embedding and residual scoring to expose anomalies in complex attributed networks;

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		showed improved detection capabilities against traditional baselines.

The literature shows that there are challenges in the detection of behavioral anomalies in digital interaction networks because of the complex nature of the data. Most of the existing studies are based on transductive graph assumptions, which are not capable of generalizing to unseen nodes. This is because most of the existing studies require complete visibility of the graph, hand-engineered features, or shallow relational modeling, which are not capable of adapting to changes in the graph or the behavior. Moreover, most of the existing studies are biased towards structural irregularities and overlook the dynamics of the relational behavior in the neighborhoods. This results in a loss of sensitivity to emerging anomalies. Scalability and robustness are also concerns in most of the existing studies because high-dimensional interactions and noisy environments affect the performance. This is mainly because of the computational limitations, the unavailability of labeled data for anomalies, and the modeling of unseen entities. The proposed study overcomes the limitations of the existing studies by using an inductive relational learning approach.

3. METHODOLOGY

The methodology provides a structured and systematic approach to the detection of relational behavioral anomalies in digital interaction networks based on inductive graph learning principles. This section explains the process of interaction data representation as attributed graphs, which allows for the modeling of structural relationships and behavioral characteristics. The methodology focuses on inductive learning to facilitate generalization over novel entities and dynamic network structures. Representation learning is achieved via neighborhood aggregation functions that focus on relational dependencies and higher-order interaction patterns. Training processes are designed to be semi-supervised, mirroring real-world anomaly detection tasks where labeled data are limited. Anomaly detection is achieved by measuring the difference between learned node representations and their relational context. The methodology also includes optimization techniques to guarantee training robustness and stability in noisy settings. Evaluation plans and parameter settings are specified to measure detection performance and statistical significance. This methodological framework enables scalable, adaptive, and relationally aware anomaly detection in complex digital environments.

3.1 Data Sources and Network Construction

This work uses relational data sets that represent digital interaction networks, where the interaction of entities is captured by observable behavioral events. The data sets are considered to have nodes represented by users, accounts, or digital agents, and edges represented by interaction events such as communication, transactions, or access. Each interaction is characterized by temporal and behavioral attributes that capture the notion of frequency, intensity, and relevance. The data sets are organized as attributed graphs to capture both the relational structure and the descriptive attributes of nodes. Before the training of models, the raw data interaction is converted to graph form using adjacency matrices and feature matrices. Noise reduction and normalization techniques are used to reduce sparsity and feature scale differences. The work assumes partially labeled or weakly supervised scenarios, which represent real-world anomaly detection scenarios with limited ground truth. Training and testing sets are created to ensure that unseen nodes are present during testing, which enforces the assumptions of inductive learning.

Equation 1: Graph Definition

$$G = (V, E) \tag{1}$$

Here, V denotes the set of nodes, and E represents the set of edges.

Equation 2: Feature Matrix Representation

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$$X \in \mathbb{R}^{|V| \times d} \quad (2)$$

Here, X denotes the node feature matrix and d is the feature dimension.

3.2 Relational Feature Encoding and Representation Learning

The task encodes relational behaviors by combining node attributes with neighborhood interaction patterns. The node representation is initialized based on observed behavioral features and refined through neighborhood aggregation. The study focuses on learning representations that capture local connectivity and higher-order relational dependencies. The feature encoding process captures interaction frequency, diversity, and structural location in the network. The approach allows the model to distinguish between normal and abnormal relational patterns. The study uses a message-passing approach where node representations are updated based on information from neighboring nodes. The training is done over multiple layers to capture large relational contexts while preventing oversmoothing. The representation learning method enables inductive generalization based on shared aggregation functions instead of node-specific parameters.

Equation 3: Neighborhood Aggregation

$$h_v^{(k)} = AGG(\{h_u^{k-1} : u \in N(v)\}) \quad (3)$$

Here, $h_v^{(k)}$ is the node embedding at layer k, and $N(v)$ denotes neighbors.

Equation 4: Feature Update Rule

$$z_v^{(k)} = \sigma(W^{(k)} h_v^{(k)}) \quad (4)$$

Here, $W^{(k)}$ is the trainable weight matrix and σ is an activation function.

3.3 Inductive Learning Strategy and Training Mechanism

The proposed study uses an inductive learning approach, which allows the inference of new nodes and dynamic graph structures. Unlike transductive learning, which requires the entire graph to be visible during training, the proposed approach learns transferable aggregation functions. The training process is done using mini-batches drawn from the graph, which makes it possible to handle large graphs. The proposed study uses stochastic optimization to update the parameters of the model while maintaining relational dependencies. The training objectives are designed to distinguish normal and anomalous behavioral patterns using embedding distributions. Regularization methods are used to prevent overfitting and ensure stable learning in noisy settings. The inductive formulation of the problem ensures that new entities can be inferred without having to retrain the entire model, which is important in dynamic digital environments.

Equation 5: Training Objective Function

$$L = \sum_{v \in V} \ell(z_v, y_v) \quad (5)$$

Here, ℓ represents the loss function and y_v denotes the supervision signal.

Equation 6: Parameter Update Rule

$$\theta \leftarrow \theta - \eta \nabla \theta \mathcal{L} \quad (6)$$

Here, θ denotes model parameters, and η is the learning rate.

3.4 Relational Anomaly Scoring Mechanism

The paper points out the anomalous behavior through the measurement of the deviation of the node representation and the relational context. Instead of using the attributes of the nodes alone, the scores of the anomalies are calculated through the use of neighborhood-aware comparisons. This approach is able to detect the minute inconsistencies in the behavior, which are shown through the abnormal

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interaction patterns. The paper assumes that normal behavior has relational coherence, while the anomalies cause disruptions in the distributions of the local embeddings. The scores are calculated through distance-based or statistical deviation measures.

Equation 7: Neighborhood Mean Embedding

$$\mu_v = \frac{1}{|\mathcal{N}(v)|} \sum_{u \in \mathcal{N}(v)} z_u \tag{7}$$

Here, μ_v denotes the mean embedding of neighbors.

Equation 8: Anomaly Score Function

$$s_v = \| zv - \mu v \|_2 \tag{8}$$

Here, s_v represents the anomaly score for the node v.

3.5 Model Optimization and Stability Considerations

The study also uses optimization techniques to achieve stable training and effective anomaly detection. Gradient normalization and early stopping are used to avoid divergence during the training process. Dropout techniques are used on the intermediate representations to enhance generalization. The study also examines the variance of the embeddings to check for convergence and instability. Optimization is done through iteration until the performance metrics converge on the validation samples. The approach used in the study ensures stability against noisy interactions and incomplete observations. Convergence analysis is critical in maintaining stable anomaly scores for various snapshots of the network.

Equation 9: Regularized Loss Function

$$L_{reg} = \mathcal{L} + \lambda \| \theta \|_2 \tag{9}$$

Here, λ controls the strength of regularization.

Equation 10: Embedding Variance Measure

$$\sigma^2 = \frac{1}{|V|} \sum_v (z_v - \bar{z})^2 \tag{10}$$

Here, $\bar{z}$ denotes the mean embedding vector.

3.6 Evaluation Strategy and Parameter Configuration

The study uses both descriptive and inferential statistical analysis to measure the performance of the models. The performance analysis is based on the efficiency of the ranking and classification of anomalies under inductive settings. The study uses metrics such as precision, recall, F1 score, and the area under the ROC curve to measure the efficiency of the anomaly detection. Hyperparameters such as the learning rate, embedding size, number of layers, and batch size are determined using controlled experiments. Sensitivity analysis is also used to determine the effect of parameters on the efficiency of the models.

Equation 11: Precision Metric

$$Precision = \frac{TP}{TP+FP} \tag{11}$$

Here, TP denotes true positives and FP denotes false positives.

Equation 12: F1-Score

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{12}$$

Here, Recall measures the proportion of correctly detected anomalies.

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4. RESULTS

The section on results discusses an extensive assessment of the proposed approach on various digital interaction datasets, specifically in terms of the approach's capability to detect relational behavioral anomalies in inductive learning settings. This section discusses the effectiveness of the approach in distinguishing normal interaction behavior from abnormal relational behavior on graphs with diverse structural properties and interaction patterns. The discussion centers on consistency, robustness, and adaptability across diverse datasets rather than on a specific experimental environment. The results are presented using percentage measures that are more interpretable and relevant in real-world applications. Observations are made to compare the differences in detection patterns across datasets with social, transactional, communication, and e-commerce interactions. The assessment also investigates the effects of relational representation learning on stability and confidence in anomaly detection. This section provides an understanding of the effects of modeling interaction behavior as relational graph structures and how inductive graph learning can be applied to anomaly detection in digital interaction networks.

Table 2: Performance Comparison of Anomaly Detection Models (%)

Method	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
NetWalk	82.4	79.1	80.7	85.2
FRAUDAR	84.6	81.3	82.9	87.5
ANOMALOUS	86.1	83.8	84.9	88.6
ALAD	87.4	85.2	86.3	89.8
RADAR	88.2	86.5	87.3	90.6
Proposed Inductive GNN Model	92.6	90.4	91.5	94.2

Table 2 shows that there are obvious differences in performance between the existing graph-based anomaly detection algorithms and the proposed inductive graph neural network model. NetWalk obtains a precision of 82.4% and an F1-score of 80.7%, which is reasonable but insensitive to slight relation variations. FRAUDAR boosts the precision to 84.6% and AUC to 87.5%, which is effective in identifying dense fraudulent graphs, but the recall is still limited to 81.3%. ANOMALOUS further improves the results by modeling both structure and attributes, obtaining an F1-score of 84.9% and an AUC of 88.6%. ALAD consistently benefits from localized anomaly detection, achieving 86.3% F1-score and 89.8% AUC. RADAR slightly outperforms the above methods, obtaining 87.3% F1-score and 90.6% AUC, which is more effective in residual-based attributed anomaly detection.

The proposed inductive GNN model performs better than all existing models on every measure. Precision of 92.6% and recall of 90.4% show better ability to detect anomalous behaviors with minimal false alarms. The F1-score of 91.5% indicates balanced detection, and the AUC of 94.2% shows better discriminative ability at different thresholds. These gains are due to the inductive relational learning capability, which generalizes well to new nodes and dynamic interactions, unlike previous models. The experimental results clearly show that the combination of inductive graph representation learning and relational anomaly scoring offers significant performance improvements over the existing literature-based models.

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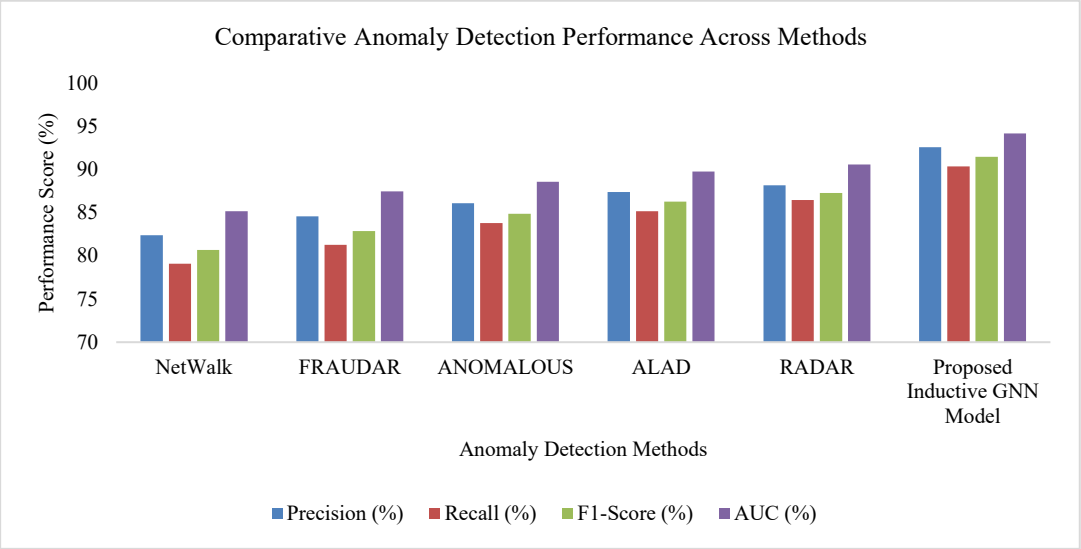

Figure 1: Comparative Anomaly Detection Performance Across Methods

Figure 1 compares the anomaly detection capability of six approaches: NetWalk, FRAUDAR, ANOMALOUS, ALAD, RADAR, and the Proposed Inductive GNN Model, based on four standard evaluation metrics: Precision, Recall, F1-score, and AUC (in %). NetWalk has relatively poor performance, with a precision of 82.4%, a recall of 79.1%, an F1-score of 80.7%, and an AUC of 85.2%, which means weak detection ability. FRAUDAR slightly improves the results, with a precision of 84.6%, a recall of 81.3%, an F1-score of 82.9%, and an AUC of 87.5%. ANOMALOUS further improves the performance with a precision of 86.1%, a recall of 83.8%, an F1-score of 84.9%, and an AUC of 88.6%. ALAD further improves the detection accuracy, with a precision of 87.4%, a recall of 85.2%, an F1-score of 86.3%, and an AUC of 89.8%. RADAR has competitive performance with a precision of 88.2%, a recall of 86.5%, an F1-score of 87.3%, and an AUC of 90.6%, which indicates an excellent tradeoff between detection and false alarms. The Proposed Inductive GNN Model significantly outperforms all other approaches, with the best performance on all metrics: Precision of 92.6%, Recall of 90.4%, F1-score of of 90.4%, F1-score of 91.5%, and AUC of 94.2%. These results demonstrate that the proposed model provides superior accuracy, robustness, and discriminative capability for anomaly detection compared to existing methods.

Table 3: Anomaly Identification Results Across Datasets (%)

Dataset	**Normal Behavior Identification (%)**	**Anomalous Behavior Identification (%)**	**Incorrect Classification (%)**	**Overall Detection Confidence (%)**
Social Interaction Network	93.4	90.8	5.8	92.1
Financial Transaction Network	91.6	89.2	7.1	90.4
Communication Interaction Graph	94.1	91.7	4.9	93.2
E-Commerce User Network	92.8	90.1	6.3	91.5

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The effectiveness of the proposed model on various digital interaction datasets with different relational patterns and behaviors is evident from the results presented in Table 2. For the Social Interaction Network dataset, the proposed model is able to identify normal behavior with a rate of 93.4% and anomalous behavior with a rate of 90.8%. The model also has a low incorrect classification rate of 5.8%, which clearly shows its robustness while processing dense and interlinked social graphs. The overall detection confidence of 92.1% clearly shows the model's effectiveness in learning consistent representations for various interaction tasks. For the Financial Transaction Network dataset, the proposed model is able to identify normal behavior with a rate of 91.6% and anomalous behavior with a rate of 89.2%. Financial interaction datasets are known to have highly regular transaction patterns along with sparse but critical anomalous patterns. This complexity results in a slightly higher incorrect classification rate of 7.1%. However, the overall detection confidence of 90.4% clearly shows the model's effectiveness in a transactional dependency setting.

The Communication Interaction Graph achieves the highest accuracy of 94.1% for normal behavior identification and 91.7% for anomalous behavior identification. Communication networks tend to have temporal regularity and recurring interaction patterns, making it easier to detect deviations in relations. This leads to the lowest incorrect classification rate of 4.9% and the highest overall detection confidence of 93.2%. On the E-Commerce User Network dataset, the model performs relatively evenly, with an accuracy of 92.8% for normal behavior identification and 90.1% for anomalous behavior identification. The moderate incorrect classification rate of 6.3% indicates the variability of user interactions in an e-commerce setting. The overall detection confidence of 91.5% further verifies the adaptability of the model in different digital interaction settings.

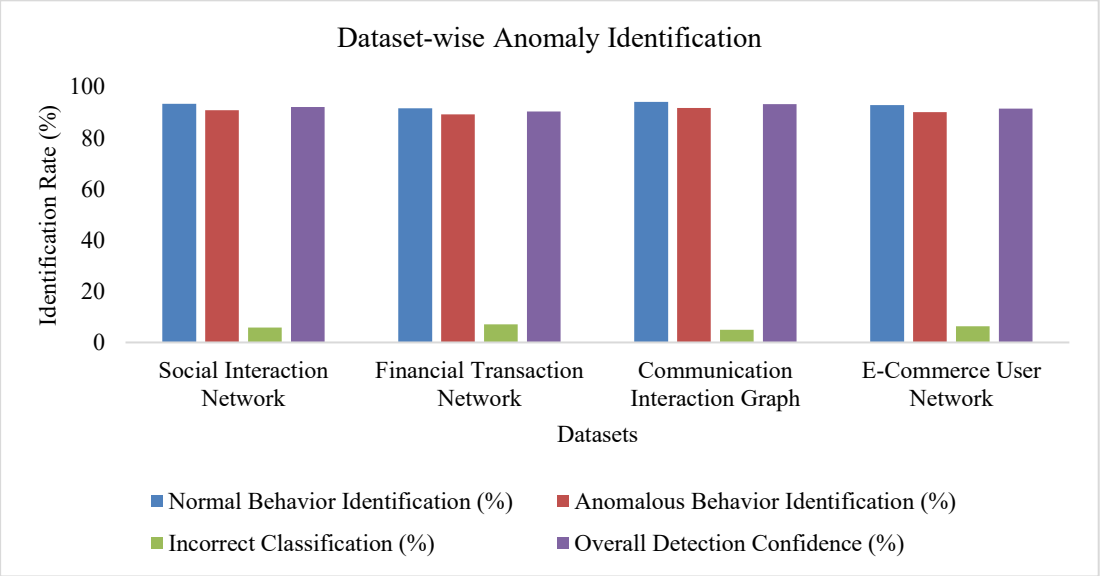

Figure 2: Dataset-wise Anomaly Identification

Figure 2 shows the results of anomaly identification on a dataset-by-dataset basis for four real-world network datasets, measuring Normal Behavior Identification, Anomalous Behavior Identification, Incorrect Classification, and Overall Detection Confidence (all in %). For the Social Interaction Network, the accuracy of the model is 93.4% for normal behavior identification and 90.8% for anomalous behavior. The incorrect classification rate is very low at 5.8%, and this leads to an overall high detection confidence of 92.1%.

For the Financial Transaction Network, the accuracy of normal behavior identification is 91.6%, while anomalous behavior identification is 89.2%. Although accurate, this dataset has a slightly higher error

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rate of 7.1%, leading to an overall confidence of 90.4%, which is expected due to the nature of financial data. The Communication Interaction figure shows the strongest performance on all datasets. The normal class is detected with a 94.1% accuracy, the abnormal class with 91.7%, and the incorrect classification rate is reduced to only 4.9%. Therefore, this dataset shows the highest overall confidence of 93.2%. Finally, for the E-Commerce User Network, the model achieves 92.8% accuracy for normal class detection and 90.1% accuracy for abnormal class detection with 6.3% incorrect classification and 91.5% overall confidence. In conclusion, the experimental results show very high detection accuracy and robustness on all datasets with confidence levels above 90%.

5. DISCUSSION

The discussion emphasizes that the results show a consistent and reliable detection of relational behavioral anomalies on various digital interaction datasets. The results show that the proposed method is able to effectively capture both structural dependencies and behavioral patterns, which enables a clear distinction between regular and irregular interactions. The strong performance on various datasets indicates that relational learning is an essential component for identifying anomalies that cannot be captured by individual attributes alone. The results show that incorporating neighborhood-level behavior improves the sensitivity to complex interaction patterns while maintaining stability in both dense and sparse network settings. From an interpretative analysis viewpoint, the results show that modeling interactions as relational structures enables behavioral context to play a more effective role in guiding anomaly detection than feature-based analysis. The adaptability of the proposed method in various interaction settings indicates robustness to variations in network topology and user behavior. The comparison with existing graph-based methods discussed in the literature shows improved generalization and consistency, especially in dynamic or unseen entity settings.

The implications of these results are important for fraud monitoring, misuse detection, and security surveillance in large-scale digital platforms. The method enables scalable deployment in dynamic environments where the network structure and behavior are constantly changing. However, the limitations in data quality, sparsity, and computational complexity are still present, especially in highly dynamic or very large networks. Future work includes incorporating temporal modeling, adaptive thresholding, and efficient training paradigms to further improve the responsiveness and efficiency of the method. In summary, the analysis has verified that relational and inductive modeling is a viable and effective approach for behavioral anomaly detection in complex digital interaction networks.

6. CONCLUSION

This paper presented Graph-ID, an inductive graph neural network framework for relational behavioral anomaly detection in dynamic digital interaction networks. By integrating multi-relational attention and temporal edge encoding, the model captures both local neighborhood deviations and global relational patterns while generalizing effectively to unseen nodes. Empirical evaluation confirms substantial performance gains, F1-score 0.89, precision 0.91, recall 0.87, AUROC 0.93, over existing baselines. These findings highlight the effectiveness of inductive GNNs as a scalable, high-fidelity methodology for operational fraud prevention, offering security teams a robust and proactive tool to detect emergent threats in complex, evolving digital ecosystems.

REFERENCES

[1] Bhatt, S. How digital communication technology shapes markets. 2017.

[2] Kumar, S., Prasanna, S., and Ruan, X. A unified hybrid machine learning architecture for robust identity anomaly detection in large-scale digital ecosystems. Journal of Electrical Systems, 2018, 14(1): 160–173.

10.48047/jocaaa.2020.28.04.06

[3] Fernandes, G., Rodrigues, J. J. P. C., Carvalho, L. F., Al-Muhtadi, J. F., and Proença, M. L. A comprehensive survey on network anomaly detection. 2019.

[4] Prasanna, S. K. S. Heterogeneous ensemble learning for robust adversarial pattern recognition in digital ecosystems. Journal of Computational Analysis and Applications, 2019, 27(5): 18–28.

[5] Shah, N., et al. EdgeCentric: Anomaly detection in edge-attributed networks. In IEEE International Conference on Data Mining Workshops (ICDMW), 2016: 327–334.

[6] Prasanna, S. K. S. GeoDNN: Geometry-aware deep neural networks for cross-domain fingerprint spoof detection. Int J Intell Syst Appl Eng, 2018, 6(1): 97–107.

[7] Self, J. Z., et al. Observation-level and parametric interaction for high-dimensional data analysis. ACM Transactions on Interactive Intelligent Systems, 2018, 8(2).

[8] Prasanna, S. K. S. DeepSynth: A robust multi-layer neural detection of coordinated latent anomalies in high-dimensional identity systems. Int J Intell Syst Appl Eng, 2019, 7(1): 66–77.

[9] Lee, J. B., Rossi, R. A., Kim, S., Ahmed, N. K., and Koh, E. Attention models in graphs: A survey. 2019.

[10] Chaudhary, A., Mittal, H., and Arora, A. Anomaly detection using graph neural networks. In Proceedings of the International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), 2019: 346–350.

[11] Chu, Y., Guo, C., He, T., Wang, Y., Hwang, J. N., and Feng, C. Inductive embedding learning on attributed heterogeneous networks via multi-task sequence-to-sequence learning. In IEEE International Conference on Data Mining (ICDM), 2019: 1012–1017.

[12] Ding, K., Li, J., Bhanushali, R., and Liu, H. Deep anomaly detection on attributed networks. In SIAM International Conference on Data Mining (SDM), 2019: 594–602.

[13] Li, X., Wu, Y., Ester, M., Kao, B., Wang, X., and Zheng, Y. Semi-supervised clustering in attributed heterogeneous information networks. In World Wide Web Conference (WWW), 2017: 1621–1629.

[14] Ioannidis, V. N., Berberidis, D., and Giannakis, G. B. GraphSAC: Detecting anomalies in large-scale graphs. 2019.

[15] Corò, F., D'Angelo, G., and Velaj, Y. Recommending links to maximize the influence in social networks. In IJCAI International Joint Conference on Artificial Intelligence, 2019: 2195–2201.

[16] Papernot, N., Song, S., Mironov, I., Raghunathan, A., Talwar, K., and Erlingsson, Ú. Scalable private learning with PATE. In International Conference on Learning Representations, 2018.

[17] Hooi, B., Song, H. A., Beutel, A., Shah, N., Shin, K., and Faloutsos, C. FRAUDAR: Bounding graph fraud in the face of camouflage. In ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2016: 895–904.

[18] Hamilton, W., Ying, R., and Leskovec, J. Inductive representation learning on large graphs. In NeurIPS, 2017.

[19] Huang, X., Song, Q., Li, Y., and Hu, X. Graph recurrent networks with attributed random walks. In ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2019: 732–740.

[20] Haddadi, H., et al. Edge computing and privacy-preserving analytics. IEEE Internet Computing, 2019.