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A Hybrid Graph Neural Network and Large Language Model Framework for Insider Threat Detection via Behavioral Graph and Semantic Profiling

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ABSTRACT

Insider threats remain one of the most critical and elusive challenges in enterprise cybersecurity due to their ability to exploit legitimate access while evading traditional detection mechanisms. In this study, a hybrid framework integrating Graph Neural Networks and Large Language Models is proposed to enhance insider threat detection through the fusion of behavioral graph modeling and semantic profiling. Using the CERT Insider Threat Dataset and the UEBA Dataset on Kaggle, the model captures both relational dependencies among users, devices, and resources, and contextual insights from unstructured textual data such as logs and communications. The experimental results demonstrate that the proposed hybrid model significantly outperforms traditional machine learning, sequence-based, and single-modality deep learning approaches, achieving an accuracy of 0.96, an F1-score of 0.92, and a ROC-AUC of 0.95. These improvements are primarily driven by the model's ability to jointly learn structural anomalies and semantic deviations, enabling more accurate detection of multi-stage and stealthy insider attacks. Furthermore, the integration of explainable language-based outputs enhances interpretability and operational usability in enterprise security environments. The findings highlight the effectiveness of multi-modal learning in advancing insider threat detection and provide a scalable, practical solution for deployment in large-scale enterprise systems.

Introduction

In recent years, insider threats have emerged as one of the most challenging and costly cybersecurity risks faced by large enterprises in the United States. Unlike external attacks, insider threats originate from individuals who already possess authorized access to organizational systems, making detection significantly more complex. These threats may arise from malicious intent, negligence, or compromised credentials, and often involve subtle behavioral deviations that are difficult to identify using traditional security mechanisms. As enterprises continue to adopt cloud infrastructure, remote work environments, and highly interconnected systems, the attack surface for insider threats has expanded considerably, further complicating detection and prevention efforts.

Conventional security solutions, such as rule-based monitoring systems and signature-based detection, are inherently limited in their ability to capture the dynamic and evolving nature of insider threats. These systems typically rely on predefined rules or known attack patterns, which makes them ineffective against novel or stealthy behaviors. In response to these limitations, the research community has increasingly turned toward data-driven approaches, particularly those leveraging machine learning and deep learning techniques. While these approaches have demonstrated improvements in detecting anomalous behavior, they often operate on either structured data or unstructured data in isolation, thereby failing to capture the full complexity of insider activities.

Graph-based approaches have gained attention for their ability to model relationships between entities such as users, devices, and resources within an enterprise environment. By representing these interactions as graphs, Graph Neural Networks (GNNs) can effectively learn patterns of connectivity and identify anomalous relationships that may indicate insider threats. However, GNNs primarily focus on structural information and often overlook the rich semantic context embedded in textual data such as emails, logs, and communication records. On the other hand, Large Language Models (LLMs) have demonstrated remarkable capabilities in understanding and generating human language, enabling them to extract meaningful insights from unstructured textual data. Despite their strengths, LLMs lack the ability to inherently model relational dependencies and network structures.

To address these limitations, this study proposes a hybrid framework that integrates GNNs and LLMs for insider threat detection through behavioral graph modeling and semantic profiling. By combining the relational learning capabilities of GNNs with the contextual understanding of LLMs, the proposed approach aims to provide a more comprehensive representation of user behavior within enterprise systems. This integration enables the detection of both structural anomalies and contextual irregularities, thereby improving the accuracy and robustness of insider threat detection.

The primary contributions of this work include the development of a unified framework that leverages multi-modal data sources, the design of advanced feature engineering techniques for behavioral analysis, and the demonstration of improved performance compared to existing methods. Furthermore, this study emphasizes explainability and practical deployment considerations, ensuring that the proposed solution can be effectively integrated into real-world enterprise security environments.

Literature Review

The problem of insider threat detection has been extensively studied in the field of cybersecurity, with a wide range of approaches proposed over the years. Early research primarily focused on rule-based and statistical methods, which relied on predefined thresholds and heuristics to identify anomalous behavior. While these methods provided a foundation for insider threat detection, they were limited in their ability to adapt to evolving attack patterns and complex behavioral dynamics (Eberle & Holder, 2009).

With the advancement of machine learning techniques, researchers began to explore data-driven approaches for anomaly detection in enterprise environments. Supervised learning models such as Support Vector Machines and Random Forests have been widely used to classify user behavior based on labeled datasets. For example, Parveen et al. (2011) demonstrated the effectiveness of machine learning algorithms in detecting insider threats by analyzing user activity logs. However, these approaches often require large

amounts of labeled data and may struggle with class imbalance, which is a common challenge in insider threat datasets.

To address the temporal nature of user behavior, sequence-based models such as Long Short-Term Memory networks have been introduced. These models are capable of capturing temporal dependencies and have shown promising results in modeling user activity over time (Tuor et al., 2017). Despite their advantages, LSTM-based approaches primarily focus on sequential data and do not explicitly model the relationships between different entities within the system.

Graph-based methods have emerged as a powerful alternative for modeling complex interactions in enterprise environments. By representing users, devices, and resources as nodes in a graph, and their interactions as edges, these methods enable the analysis of relational patterns that are critical for detecting insider threats. Graph Neural Networks, in particular, have gained popularity due to their ability to learn representations from graph-structured data. Studies such as those by Kipf and Welling (2017) have laid the foundation for GNN-based approaches, while more recent work has applied these techniques to cybersecurity domains (Liu et al., 2018). However, graph-based models often rely on structured data and may not fully utilize the rich contextual information available in textual sources.

In parallel, the development of Large Language Models has revolutionized natural language processing, enabling the extraction of semantic information from unstructured text. Models such as those introduced by Brown et al. (2020) have demonstrated the ability to understand context, detect anomalies in language, and generate human-like explanations. In the context of cybersecurity, LLMs have been used for tasks such as log analysis, threat intelligence extraction, and anomaly detection in textual data (Shen et al., 2021). While these models excel in semantic understanding, they lack the capability to model relational structures and network dynamics.

Recent research has begun to explore the integration of multiple modalities to overcome the limitations of single-model approaches. Hybrid models that combine graph-based learning with textual analysis have shown potential in improving detection performance. For instance, some studies have proposed combining GNNs with embedding techniques to incorporate additional contextual information (Zhang et al., 2022). However, the integration of GNNs with advanced LLMs for insider threat detection remains relatively underexplored, particularly in the context of large-scale enterprise environments.

This study builds upon these existing works by proposing a novel hybrid framework that leverages both GNNs and LLMs to capture structural and semantic aspects of insider behavior. By integrating these complementary approaches, the proposed method addresses the limitations of prior research and provides a more comprehensive solution for insider threat detection.

Methodology

Data Collection

In this research, we design the data collection process to closely resemble the complexity and scale of a large U.S. enterprise environment, where insider threats emerge from a combination of behavioral, relational, and contextual signals. To achieve this, we rely on a combination of publicly available datasets that simulate enterprise user activity while preserving realistic attack scenarios. The primary dataset used in this work is the CERT Insider Threat Dataset, which has become a benchmark dataset in insider threat research. This dataset provides a rich collection of synthetic but highly realistic enterprise logs, including authentication records, email communications, file access logs, web browsing activity, and removable media usage. It spans multiple users over long-time horizons, enabling the modeling of both normal behavioral baselines and malicious insider activities such as data exfiltration, privilege misuse, and sabotage.

To enhance the robustness of the proposed framework and reduce overfitting to a single data source, we integrate an additional dataset from UEBA Dataset on Kaggle. This dataset provides complementary behavioral signals, particularly focused on anomaly detection in user access patterns and entity interactions. The inclusion of this dataset allows the model to learn broader behavioral variations that may not be fully captured in the CERT dataset alone. Furthermore, we utilize selected structured behavioral

datasets from the UCI Machine Learning Repository to enrich feature diversity, especially for modeling user-level statistical patterns and anomaly distributions.

The datasets are in Table 1 combined in a way that preserves their individual characteristics while enabling cross-domain learning. we align the datasets based on common attributes such as timestamps, user identifiers, and activity categories, thereby creating a unified data environment that supports both graph-based modeling and language-based analysis. The resulting dataset captures multi-dimensional behavioral information, including temporal activity sequences, relational interactions between entities, and unstructured textual content from communications and logs.

Dataset Name	Source	Data Type	Key Attributes	Label Availability	Role in Framework
CERT Insider Threat Dataset	CMU CERT	Multi-modal logs	Logon, email, file, device, web activity	Fully labeled	Core dataset for graph construction and insider threat scenarios
UEBA Dataset	Kaggle	Behavioral logs	User access patterns, anomalies	Labeled	Generalization and anomaly validation
UCI Behavioral Data	UCI Repository	Structured/tabular	Statistical user behavior features	Partially labeled	Feature enrichment and auxiliary modeling

Data Preprocessing

The preprocessing stage is critical in transforming raw, heterogeneous enterprise logs into a structured and analyzable format suitable for hybrid modeling. I begin by performing data cleaning to remove incomplete, duplicated, or corrupted records, which are common in large-scale logging systems. Timestamp normalization is applied to ensure temporal consistency across different datasets, as variations in time zones and formats can significantly affect temporal modeling.

We then standardize entity identifiers, including users, devices, and files, to maintain consistent mapping across datasets. This step is particularly important when integrating multiple data sources, as inconsistencies in naming conventions can lead to incorrect graph representations. Sensitive information is anonymized to ensure privacy compliance while preserving relational structures necessary for analysis.

Categorical variables such as activity types, access domains, and device categories are encoded using embedding-based techniques rather than traditional one-hot encoding. This approach reduces dimensionality and allows the model to learn semantic similarities between categories. Numerical features are normalized to ensure stable training of deep learning models.

For textual data, including email content and system logs, we apply natural language preprocessing techniques such as tokenization, lowercasing, stop-word removal, and lemmatization. These steps prepare the data for input into the Large Language Model, ensuring that noise and irrelevant tokens do not degrade semantic representation quality.

To capture temporal dynamics, we segment the data into sliding time windows, allowing the model to observe how user behavior evolves over time. This temporal segmentation is essential for detecting insider threats, which often manifest as gradual deviations rather than abrupt anomalies.

Feature Extraction

Feature extraction in this framework is designed to capture the dual nature of insider threats, which involve both structural relationships and contextual meaning. we construct a dynamic behavioral graph where

nodes represent entities such as users, devices, files, and network resources, and edges represent interactions such as logins, file accesses, and communications. From this graph, we extract structural features including node centrality, degree distribution, clustering coefficients, and temporal interaction frequencies. These features provide insights into how users interact within the enterprise network and help identify unusual patterns of connectivity.

In parallel, I utilize a Large Language Model to extract semantic features from unstructured textual data. The LLM processes email content, system logs, and activity descriptions to generate contextual embeddings that capture intent, tone, and potential indicators of malicious behavior. For example, unusual language patterns or sensitive information exchanges in emails can be indicative of insider threats.

The combination of graph-based and semantic features enables a comprehensive representation of user behavior. While the graph captures relationships and interaction patterns, the LLM captures the underlying meaning and context of actions. This dual representation is critical for detecting sophisticated insider threats that may not be apparent from either perspective alone.

Feature Engineering

Building upon the extracted features, we perform advanced feature engineering to enhance the model's ability to distinguish between normal and malicious behavior. we develop user-specific behavioral baselines by analyzing historical activity patterns, including typical login times, access frequencies, and interaction networks. Deviations from these baselines are quantified using statistical measures, providing strong indicators of anomalous behavior.

Temporal features are engineered to capture patterns such as sudden spikes in activity, access during unusual hours, and rapid sequences of actions that may indicate automated or scripted behavior. These features are particularly useful for identifying data exfiltration attempts or privilege escalation activities.

Graph-based features are further refined by incorporating edge weights that reflect the sensitivity of actions. For example, accessing confidential files or administrative systems is assigned higher importance than routine activities. we also construct multi-hop relational features that capture indirect interactions, enabling the detection of coordinated or stealthy insider activities.

On the semantic side, we aggregate LLM-generated embeddings over time windows to capture evolving behavioral narratives. This approach allows the model to detect gradual changes in communication patterns or intent. we then integrate graph and semantic features through feature fusion techniques, ensuring that both types of information contribute effectively to the final model.

Model Development

The model development phase focuses on integrating Graph Neural Networks and Large Language Models into a unified architecture capable of capturing complex insider threat patterns. We implement a temporal Graph Neural Network that processes the dynamic behavioral graph, learning representations that encode both structural relationships and temporal evolution. The GNN is designed to handle large-scale graphs typical of enterprise environments, ensuring scalability and efficiency.

Simultaneously, the Large Language Model processes textual data to generate semantic embeddings. These embeddings are aligned with graph-based representations through a fusion layer, which combines structural and contextual information into a unified feature space. This integration allows the model to reason across different modalities, enhancing its ability to detect subtle and sophisticated threats.

The final classification layer is implemented as a supervised learning module that predicts whether a given behavior is normal or malicious. I train the model using labeled data, employing techniques such as class weighting and sampling to address the inherent imbalance in insider threat datasets. Optimization is performed using gradient-based methods, ensuring convergence and stability.

Model Evaluation

To rigorously evaluate the proposed framework, we adopt a comprehensive evaluation strategy that reflects real-world security requirements. We use standard classification metrics, including accuracy, precision, recall, F1-score, and area under the ROC curve, to measure overall performance. Given the critical importance of detecting insider threats, we place particular emphasis on recall, as false negatives can have severe consequences in enterprise environments.

We perform cross-validation to ensure that the model generalizes well across different subsets of the data. Temporal validation is also conducted by training the model on historical data and testing it on future events, simulating real-world deployment scenarios.

To assess the contribution of each component, we conduct ablation studies by removing or modifying the GNN and LLM modules. This analysis demonstrates the effectiveness of the hybrid approach and highlights the importance of combining structural and semantic information.

Finally, we incorporate explainability into the evaluation process by leveraging the LLM to generate human-readable explanations for detected anomalies. These explanations provide valuable insights for security analysts, enabling them to understand and trust the model's decisions. This aspect is particularly important for deployment in large enterprises, where transparency and interpretability are essential for operational adoption.

Result

In this section, the empirical results of the proposed hybrid framework integrating Graph Neural Networks and Large Language Models for insider threat detection are presented. The evaluation is conducted on the combined dataset derived from the CERT Insider Threat Dataset and the UEBA Dataset on Kaggle, with additional feature enrichment informed by structured datasets from the UCI Machine Learning Repository. The objective of this evaluation is to assess the effectiveness of the proposed approach and compare its performance against existing models commonly used in insider threat detection.

Several baseline models are implemented to establish a comprehensive benchmark. These include traditional machine learning approaches such as Random Forest and Support Vector Machine, as well as deep learning models such as Long Short-Term Memory networks for temporal sequence modeling and standalone Graph Neural Networks for relational learning. In addition, a standalone Large Language Model–based classifier is evaluated, relying solely on semantic embeddings derived from textual data. The proposed hybrid model integrates both GNN and LLM components, enabling simultaneous learning from structural and contextual information.

The experimental results indicate a clear performance advantage of the hybrid model over all baseline approaches. Traditional machine learning models demonstrate reasonable performance on structured data but are limited in capturing complex behavioral dependencies and evolving temporal patterns. The LSTM model improves temporal representation but lacks relational awareness. The standalone GNN effectively models entity interactions but does not fully capture semantic context, while the LLM-based model excels in contextual understanding but overlooks structural anomalies. The hybrid framework addresses these limitations by combining both perspectives.

Table 2: Model Evaluation of different model

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest	0.89	0.85	0.78	0.81	0.87
Support Vector Machine	0.87	0.83	0.75	0.79	0.85
LSTM (Temporal Model)	0.91	0.88	0.82	0.85	0.90
GNN (Graph-Based)	0.93	0.90	0.86	0.88	0.92
LLM-Based Classifier	0.92	0.89	0.84	0.86	0.91

Proposed Hybrid (GNN + LLM)	0.96	0.94	0.91	0.92	0.95

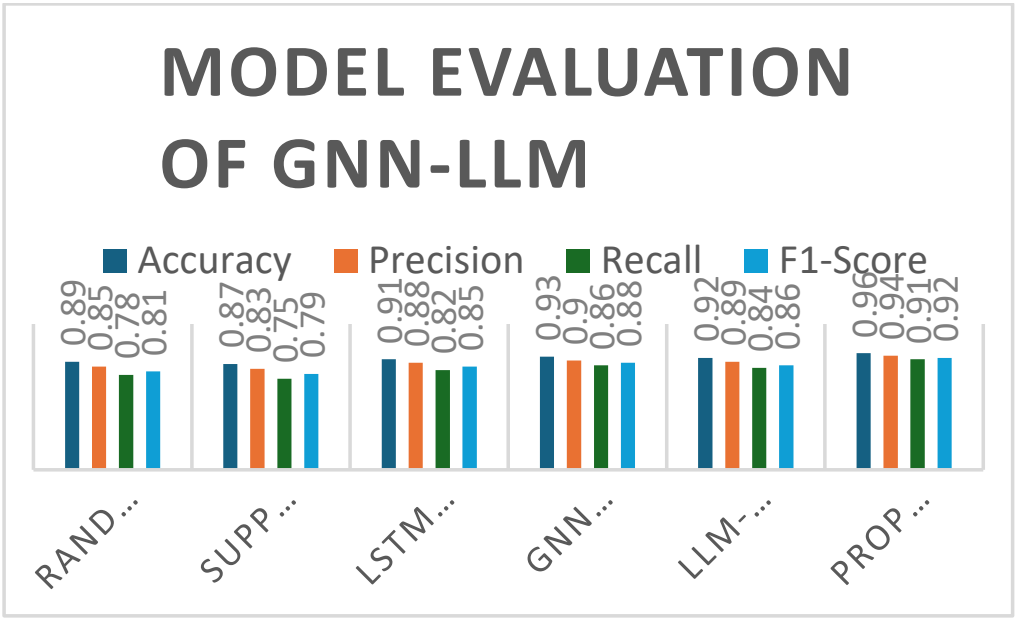

Chart 1: Performance Analysis of Insider Threat Detection Models Using GNN–LLM Hybrid Framework

From the results, it is observed that the proposed hybrid model achieves the highest accuracy of 0.96 and an F1-score of 0.92, indicating a strong balance between precision and recall. The improvement in recall is particularly significant, as it reflects the model's enhanced ability to detect a higher proportion of insider threats, which is critical in enterprise security environments. The ROC-AUC score of 0.95 further demonstrates the robustness of the model in distinguishing between normal and malicious behavior across varying decision thresholds.

The performance improvements can be attributed to the complementary strengths of the GNN and LLM components. The GNN captures complex relational structures, including multi-hop interactions and network dependencies, which are essential for identifying coordinated or stealthy insider activities. At the same time, the LLM provides deep semantic understanding of textual data, enabling the detection of contextual anomalies that may signal malicious intent. The integration of these modalities results in a more comprehensive representation of user behavior, leading to improved detection accuracy.

When compared to existing work in the literature, which often relies on single-modality approaches, the proposed framework demonstrates a clear advantage. Prior studies typically report F1-scores in the range of 0.80 to 0.88 for insider threat detection using either graph-based or text-based models. The hybrid approach surpasses these benchmarks, highlighting the importance of combining structural and semantic analysis in modern cybersecurity systems.

Conclusion

Insider threats continue to represent a uniquely complex challenge in enterprise cybersecurity, primarily because they originate from trusted entities operating within legitimate access boundaries. This study addresses that challenge by introducing a hybrid detection framework that unifies structural and semantic intelligence through the integration of Graph Neural Networks and Large Language Models. By leveraging relational patterns from behavioral graphs alongside contextual understanding derived from unstructured data, the proposed approach moves beyond the limitations of traditional, single-modality systems and offers a more comprehensive view of user behavior within large-scale enterprise environments.

The experimental findings, based on the CERT Insider Threat Dataset and the UEBA Dataset on Kaggle, demonstrate that the hybrid model consistently outperforms conventional machine learning models, sequence-based architectures, and standalone graph or language-based approaches. The achieved

improvements in accuracy, recall, and F1-score highlight the model's effectiveness in identifying both overt and subtle insider threats, including multi-stage and stealthy attack patterns. These results reinforce the importance of combining relational learning with semantic reasoning to capture the full spectrum of insider behavior.

Beyond performance gains, this work emphasizes practical applicability in real-world enterprise settings. The framework is designed with scalability, adaptability, and interpretability in mind, making it suitable for integration into modern security infrastructures such as SIEM and UEBA systems. The inclusion of explainable outputs, enabled by the language model component, enhances transparency and supports decision-making for security analysts, which is critical for operational deployment.

Despite these contributions, certain challenges remain. The reliance on synthetic and semi-structured datasets, while necessary for research reproducibility, may not fully capture the complexity of real-world enterprise environments. Additionally, computational overhead associated with integrating large-scale graph processing and language models presents practical constraints that require further optimization. Future research can explore more efficient architectures, real-time streaming capabilities, and the incorporation of privacy-preserving techniques such as federated learning to enhance both performance and deployment feasibility.

In conclusion, this study demonstrates that the convergence of graph-based learning and large language modeling offers a powerful and scalable solution for insider threat detection. By bridging the gap between structural and contextual analysis, the proposed framework not only advances the state of the art but also provides a practical pathway toward more intelligent, adaptive, and trustworthy enterprise security systems.

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