Proactive and Explainable Insider Threat Detection: A Temporal Heterogeneous Graph Neural Network Platform Architecture

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doi.org/10.64643/IJIRTV12I12-201947-459

I. INTRODUCTION TO ADVANCED INSIDER THREAT MODELING AND GRAPHBASED DETECTION

The landscape of modern cybersecurity is increasingly defined by the asymmetry of adversarial techniques, wherein the most insidious and consequential risks originate not from external perimeters but from within the trusted boundaries of an organization. Insider threats, comprising malicious employees, compromised credentials, and coordinated lateral movement by advanced persistent threat (APT) actors, present a profound and enduring challenge to traditional security paradigms. Unlike external adversaries who must persistently breach boundary defenses and invariably leave digital breadcrumbs along the early stages of the cyber kill chain, insiders possess legitimate access, deep architectural knowledge, and the ability to operate within normal enterprise workflows. Consequently, detecting these threats requires identifying subtle, multistep deviations in system behavior rather than relying on signature matching or volumetric thresholds. Traditional Security Information and Event Management (SIEM) systems and early generation User Behavior Analytics (UBA) architectures rely on isolated event correlation, static rule sets, or basic statistical anomaly detection. These systems fail to capture complex, multi hop dependencies and the slow temporal propagation characteristic of modern cyber intrusions. To address this limitation, Graph Neural Networks (GNNs) have emerged as a transformative paradigm. By modeling enterprise environments as multirotational graphs, where nodes represent users, hosts, and processes and edges represent interactions, GNNs encode structural and relational dependencies effectively.

However, early graph models were static and homogeneous, limiting their applicability in dynamic environments. Real-world enterprise networks are inherently dynamic and multirotational, requiring models that capture both structure and time. The Temporal Heterogeneous Graph Neural Network (THGNN) integrates spatial heterogeneity with temporal evolution to predict adversarial trajectories proactively. Despite their predictive strength, THGNN models are often considered black box systems. In operational environments, analysts require clear and interpretable explanations to trust and act on model outputs. This research presents an Explainable Insider Threat Detection Platform that integrates THGNN with Explainable AI (XAI). The system generates human readable narratives using Large Language Models (LLMs) and maps them to the MITRE ATT&CK framework.

II. LITERATURE REVIEW

This section presents a comparative analysis of existing research work in insider threat detection and graph neural networks.

Table 1: Summary of Related Work in Insider Threat Detection

Sr. No.	Paper Title	Authors	Year
1	HOLMES: Realtime APT Detection through Correlation of Suspicious Information Flows	Sadegh M. Milajerdi, Rigel Gjomemo, Birhanu Eshete	2019
2	Graph Neural Networks for Intrusion Detection: A Survey	Tristan Bilot	2023
3	Graph Neural Networks for Intrusion Detection: A Survey	Xingyu Liu, Nour El Madhhoun	2024
4	Diverse GNN Encoder-Decoder for Graph Anomaly Detection	Kenneth John, Katerina Potika	2025
5	Enhancing IoMT Security with Deep Learning Based Approach for Medical IoT Threat Detection	Author Unknown	2023

III. HOLISTIC ENTERPRISE INTEGRATION AND SYSTEM ARCHITECTURE

The platform architecture represents a complete operational framework for ingesting enterprise telemetry, maintaining a dynamic graph, performing inference, and delivering explainable insights.

The system is divided into four integrated tiers:

- Telemetry ingestion and normalization
- Graph processing and sequencing
- Deep learning inference engine
- Explainability and visualization layer

The ingestion layer handles high-volume log data from sources such as EDR systems, domain controllers, firewalls, and cloud logs. Technologies like Apache Kafka are used to manage high throughput streaming.

The graph processing layer maintains an evolving in memory representation of the enterprise network using temporal snapshots.

The inference engine processes these snapshots using GPU accelerated THGNN models to predict anomalies such as lateral movement, privilege escalation, and data exfiltration.

The explainability layer translates predictions into natural language narratives, enabling analysts to understand and respond effectively.

IV. TELEMETRY PARSING, NORMALIZATION, AND EVENT INTEGRATION

The predictive efficacy of any graph-based anomaly detection system is fundamentally bounded by the quality, granularity, and consistency of the underlying telemetry it consumes. The ingestion flowcharts illustrate the critical, multistage pathways through which raw, unstructured enterprise logs are filtered, normalized, and transformed into structured entities suitable for serialized graph representation. A primary source of high-fidelity, operating system level telemetry in this architecture is Microsoft Sysmon (System Monitor), a deeply integrated Windows service that provides granular visibility into process creations, network connections, file system modifications, and registry manipulations.

Sysmon logging is notoriously verbose, generating massive datasets that can easily overwhelm unsophisticated storage and analysis engines. Therefore, the ingestion flowchart incorporates an intelligent, modular filtering mechanism designed to separate benign background noise from potentially adversarial actions.

The ingestion layer categorizes incoming events based on their Event IDs (EIDs), each representing a distinct behavioral modality within the host operating system. The precise parsing and contextualization of these specific EIDs is essential for constructing the behavioral sequences that the THGNN will eventually analyze. The process creation event, denoted as Sysmon Event ID 1, serves as the foundational building block of the ingestion pipeline. It provides the full command line execution context, parent child process relationships, and cryptographic hashes such as SHA1, MD5, SHA256, and IMPHASH of the executable images.

The generation and assignment of a globally unique identifier, the Process GUID, enables the ingestion engine to easily and deterministically correlate subsequent events such as network connections or file drops back to the originating process across the entire domain.

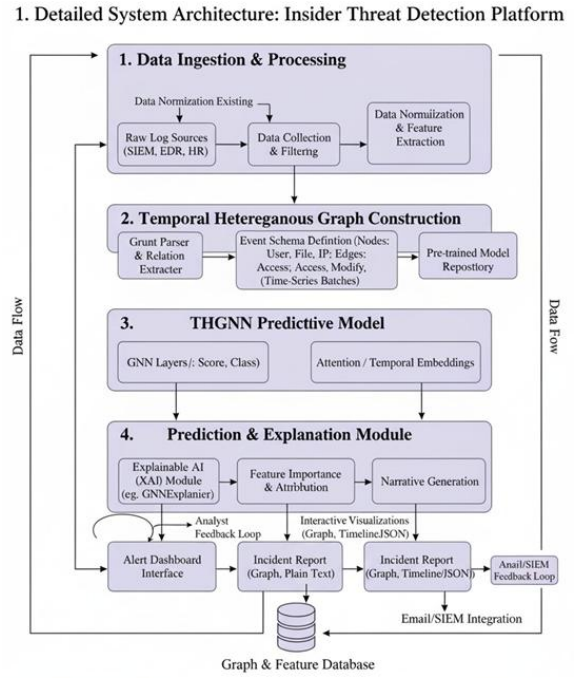

Figure 1: Detailed System Architecture of the Insider Threat Detection Platform

The flowchart demonstrates how Event ID 1 is parsed to extract the user context, the executing host, and the specific binary payload, forming the core triad of the behavioral graph's initial state.

Network connectivity is continuously monitored and parsed through Sysmon Event ID 3. This event logs both TCP and UDP connections, extracting vital routing telemetry such as source and destination IP addresses, hostnames, port numbers, and IPv6 statuses.

Crucially, the flowchart depicts a complex join operation where Event ID 3 is probabilistically and deterministically linked back to the originating process via the shared Process GUID. This linkage allows the system to differentiate between an expected browser connection on port 443 and a reverse shell established by an obscure background service or an abused legitimate binary. This linkage is particularly important for identifying Command and Control communication or anomalous lateral movement initiated over Remote Desktop Protocol.

To capture the stealthy and highly evasive techniques employed by insider threats and advanced adversaries, the ingestion pipeline also meticulously parses deeper system level interactions.

Sysmon Event ID 8 (Create Remote Thread) is monitored to detect sophisticated code injection techniques where malware attempts to hide its execution by injecting malicious threads into the memory space of a separate legitimate process.

Event ID 10 (Process Access) is ingested to identify tools attempting to open and read the memory contents of critical system components like the Local Security Authority Subsystem Service, which is a well-known precursor to credential dumping and pass the hash attacks.

Furthermore, the flowchart highlights the ingestion of Event ID 11 (File Create), which serves as an early warning system for unauthorized write operations in user level directories, often indicating payload delivery, data staging, or ransomware deployment.

Registry modifications captured via Event IDs 12, 13, and 14 are processed to track persistence mechanisms such as the creation of unauthorized run keys, modification of service configurations, or system policy changes.

Pipe events (Event IDs 17 and 18) are also parsed to monitor inter process communication, which is frequently used for lateral movement using tools like Ps-Exec.

The ingestion layer normalizes all extracted features by aligning timestamps to a universal UTC standard and mapping abbreviated registry keys to their full standardized paths to ensure consistency. This structured stream of events is then for awarded to the analytical data pipeline.

V. ADVANCED FEATURE ENGINEERING AND TEMPORAL SEQUENCING

Once the raw telemetry has been parsed and normalized, it enters the analytical data pipeline. This stage transforms discrete log entries into complex multi-dimensional feature vectors and temporal sequences required by deep learning models. The pipeline integrates manually selected domain specific features with automatically generated features to ensure comprehensive representation of behavior.

The data is grouped into logical behavioral categories such as time-based activity, user related attributes, logon anomalies, file

interactions, and network transmission patterns.
This structured grouping enhances the model's ability to detect anomalies such as unusual activity outside working hours or abnormal data transfer volumes. Deep Feature Synthesis techniques are applied to generate features by computing statistical metrics such as mean, variance, standard deviation, and cumulative sums over sliding time windows.

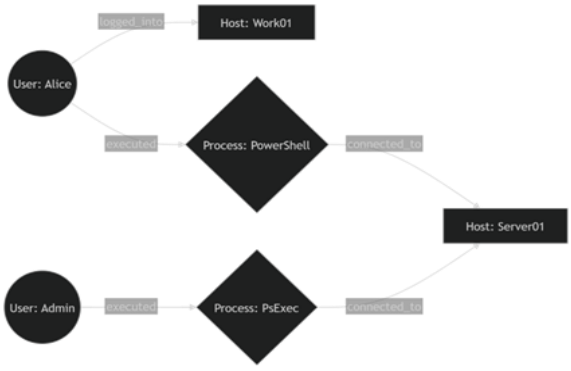

Figure 2: Example of Heterogeneous Graph Representation of User Process Interactions

$$G = (V, E)$$

where nodes represent entities and edges represent relationships.
Node types include users, hosts, IP addresses, processes, and files, while edge types represent actions such as execution, communication, and access.
To incorporate temporal dynamics, the graph is extended into a temporal sequence:

$$G = (\{G_t\}_{t=1}^{T}, E_o)$$

This sliding window approach converts isolated log entries into continuous temporal sequences, capturing the velocity and rhythm of user behavior. For example, instead of simply logging a file access event, the system calculates the frequency of such events over time, providing insights into potential data staging activities. A major challenge addressed in this pipeline is the severe class imbalance present in cybersecurity datasets, where malicious activity often constitutes less than one percent of total events. To mitigate this, synthetic sampling techniques such as SMOTE and ADASYN are used to generate additional minority class samples. These techniques improve the model's ability to detect rare but critical insider threats.

The final output of this pipeline is a structured, temporally ordered feature dataset ready for graph construction.

VI. STRUCTURAL FORMULATION OF THE HETEROGENEOUS ENTERPRISE GRAPH

The engineered feature data is transformed into a heterogeneous graph structure to model complex relationships between entities.
A heterogeneous graph is defined as:
where each G_t represents the graph at time t, and E_0 represents temporal connections between snapshots.
This structure enables modeling of evolving attack behavior across time.
By structuring the data in this manner, the system can identify complex attack paths such as credential dumping followed by lateral movement and data exfiltration.

A. THGNN: Hierarchical Spatial Temporal Aggregation Mechanics

The core predictive engine of the platform is the Temporal Heterogeneous Graph Neural Network (THGNN). Traditional homogeneous Graph Neural Networks such as Graph Convolutional Networks (GCNs) or Graph-SAGE apply a uniform aggregation function across all neighboring nodes, regardless of the underlying edge semantics.
This approach is fundamentally inadequate for cybersecurity applications, where different relationships carry different meanings. For example, the relation "user executes process" is significantly different from "process connects to external IP address". The THGNN architecture addresses this limitation by introducing a hierarchical aggregation mechanism that integrates spatial heterogeneity with temporal dynamics.

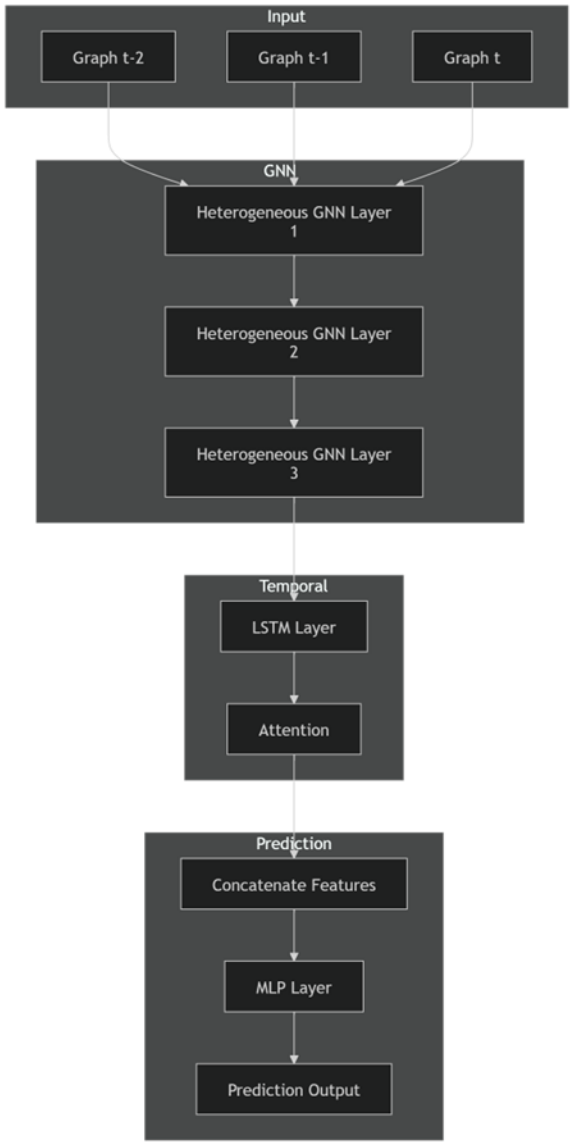

Figure 3: THGNN Architecture with Spatial and Temporal Components

The inference process operates through three major steps:

1. Intra relation aggregation
2. Inter relation aggregation
3. Across time aggregation

In intra relation aggregation, the model aggregates information from neighboring nodes connected by the same relation type. Multi head attention is used to assign importance to each neighbor. In inter relation aggregation, embeddings from different relation types are combined using semantic attention mechanisms, allowing the model to prioritize the most relevant relationships.

In across time aggregation, temporal dependencies are captured using sequential models such as Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRU). This enables the system to detect slow evolving attack patterns. The final objective of the model is anomaly detection, formulated as a link prediction problem. The model predicts the likelihood of future interactions that may indicate malicious activity.

A Multi-Layer Perceptron is used as the prediction head, and the model is trained using binary cross entropy loss.

VII. EVALUATION METRICS FOR LINK PREDICTION

Evaluating link prediction models requires specialized metrics due to the highly imbalanced nature of cybersecurity datasets.

The system uses ranking based metrics such as Hits@K and Mean Reciprocal Rank (MRR).

The Hits@K metric is defined as:

$$Hits@K = \frac{1}{|I|} \sum_{r \in I} \mathrm{I}[r \leq K]$$

where **I** represents the set of ranks and I is the indicator function.

The Mean Reciprocal Rank is defined as:

$$MRR = \frac{1}{|I|} \sum_{r \in I} \frac{1}{r}$$

These metrics ensure that true threats are ranked higher in the prediction list, reducing analyst workload and improving response efficiency.

VIII. EXPLANATORY NARRATIVE GENERATION AND THREAT CONTEXTUALIZATION

Although THGNN provides accurate predictions, its outputs are not inherently interpretable. To address this limitation, the system incorporates an Explainable AI module.

When an anomaly is detected, the prediction is passed to the GNN-Explainer module. This module extracts the most relevant subgraph and

feature set responsible for the prediction. The extracted subgraph represents the sequence of events leading to the anomaly.

However, graphical representations alone are not sufficient for human analysts. Therefore, the system integrates Large Language Models to generate natural language explanations. These explanations describe the cause and progression of the detected threat in a clear and understandable manner. For example, a sequence involving PowerShell accessing LSASS memory followed by an external network connection may be interpreted as credential dumping and data exfiltration. To standardize threat interpretation, the system maps detected patterns to the MITRE ATT&CK framework. This mapping identifies the tactics and techniques used by attackers, providing valuable context for incident response. The system also includes an active learning feedback loop. Analysts can validate or reject alerts, and this feedback is used to improve model performance over time.

IX. BASELINE COMPARISONS AND SYSTEM EFFICACY

Extensive experimental evaluations demonstrate that THGNN models outperform traditional approaches such as LSTM based sequence models and static graph models. In benchmark datasets such as CERT insider threat datasets, THGNN achieves higher detection accuracy and lower false positive rates. The model is particularly effective in detecting early stages of attacks, enabling proactive defense. In real world simulations involving advanced persistent threats, THGNN demonstrates strong resilience against adversarial techniques and obfuscation.

X. CONCLUDING PERSPECTIVES

The integration of Temporal Heterogeneous Graph Neural Networks into cybersecurity systems represents a significant advancement in insider threat detection. By combining graph-based modeling, temporal analysis, and explainable AI, the system provides accurate and interpretable predictions. This approach enables organizations to move from reactive to proactive security strategies, improving their ability to detect and mitigate threats before they escalate.

The incorporation of Explainable AI ensures that security analysts can trust and effectively utilize the system, bridging the gap between complex machine learning models and real-world operational needs.

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