AI-Based Insider Threat Detection in Cloud

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Abstract - This study proposes a federated transformer–graph neural network (GNN) framework for zero-trust insider threat detection in multi-cloud environments, enhancing privacy-preserving and real-time behavioral analytics. The approach combines LSTM autoencoders for analysing sequential logs, GNNs for modelling user-network interactions, and reinforcement learning for setting adaptive risk thresholds. It is trained using augmented CERT Insider and CSE-CIC-IDS2018 datasets through federated learning across simulated AWS/Azure/GCP environments. The experimental findings reveal outstanding performance, achieving a 97% AUC-ROC, a 15% reduction in false positives, and a 10% increase in accuracy compared to previous hybrid ML/DL baselines. This framework facilitates proactive detection of insider actions such as privilege escalation and data exfiltration while maintaining GDPR-compliant privacy through differential mechanisms. These innovations provide scalable, explainable AI solutions for enterprise multi-cloud security, overcoming the limitations of traditional UEBA with modern zero-trust architectures and setting the stage for autonomous threat mitigation systems.

Key Words Insider Threat Detection, Zero-Trust Architecture, Federated Learning, Graph Neural Networks (GNN), Cloud Security, Anomaly Detection, User and Entity Behavior Analytics (UEBA), Differential Privacy, Multi-Cloud Security, Deep Learning.

1. INTRODUCTION

The strategic necessity for modern businesses to embrace multi-cloud environments is driven by the need for scalability, redundancy, and operational efficiency. However, the inherent distributed and shared characteristics of cloud platforms present distinct security challenges that traditional perimeter-based security measures are ill-equipped to handle. Insider threats, which originate from authorized individuals such as employees, contractors, or partners, pose significant risks as they can use legitimate credentials to circumvent standard security measures. This situation calls for more adaptive and sophisticated security solutions that are specifically designed to address the dynamic and complex nature of cloud infrastructures.

Artificial intelligence (AI) has become a game-changing technology in enhancing cloud security frameworks, especially in identifying and mitigating insider threats. AI-driven systems, utilizing machine learning and deep learning algorithms, are capable of continuously analysing large volumes of network and user behaviour data in real-time, allowing for the detection of subtle anomalies that may suggest malicious intent. Incorporating AI into zero-trust architectures, which focus on continuous verification, least-privilege access, and micro segmentation, further bolsters defence mechanisms within multi-cloud environments. These AI-based strategies not only enhance the detection of known threats but also provide the ability to anticipate and counter new attack vectors, addressing the limitations of static, rule-based traditional security systems.

Despite challenges such as model complexity, data privacy issues, and potential biases in AI algorithms, the benefits of integrating AI into cloud security—such as adaptability, speed, and accuracy—make it essential for contemporary cybersecurity strategies. Additionally, evolving regulatory requirements are prompting cloud service providers to adopt advanced AI technologies to ensure compliance and safeguard sensitive data. This research examines the application of AI methodologies in detecting insider threats within zero-trust multi-cloud infrastructures, aiming to bridge the gap between traditional security controls and adaptive, AI-driven monitoring to enhance the overall security posture of cloud computing environments.

2. Literature Review

AI and machine learning (ML) have transformed cybersecurity in cloud environments by facilitating automated and adaptive threat detection. This technology processes large datasets to uncover patterns, anomalies, and behavioral deviations that go beyond traditional signature-based methods. Foundational surveys, such as those by Buczak and Guven (2016), have evaluated ML techniques like decision trees, support vector machines (SVMs), random forests, and neural networks, emphasizing the trade-offs in terms of accuracy, efficiency, and interpretability.

Supervised learning is particularly effective at classifying known attacks using labeled data. Ensemble methods, such as random forests and gradient boosting, have shown resilience against imbalanced datasets and adversarial evasion (Apruzzese et al., 2018). Unsupervised methods, including K-means, DBSCAN, isolation forests, and autoencoders like Kitsune (Mirsky et al., 2018), are capable of detecting new zero-day threats without labels by identifying deviations from normal behavior, which is essential in dynamic cloud environments.

Deep learning, through convolutional and recurrent neural networks (RNNs/LSTMs), captures temporal patterns in network flows, API calls, and system events, surpassing traditional ML in handling unstructured data (Kwon et al, 2019). Reinforcement learning (Nguyen and Reddi, 2021) and transfer learning provide adaptive, experience-based defenses against evolving threats, addressing data scarcity by using pre-trained models that are fine-tuned for security purposes.

Advanced AI frameworks compile real-time logs, traffic, and VM data; incorporate global threat intelligence; apply continuous supervised and unsupervised model inference; conduct behavior analytics to detect anomalies like insider actions or zero-days; and initiate automated responses such as IP blocks or isolations, thereby supporting proactive security measures.

Insider threats can be categorized as malicious (intentional data theft or sabotage for personal gain or revenge, such as the 2018 Tesla code tampering), negligent (careless mistakes like the 2019 Capital One misconfiguration that exposed 100 million records), and compromised (hijacked credentials through phishing or malware that enable stealthy lateral movement). Cloud-specific challenges include visibility gaps in hybrid or multi-cloud environments, shadow IT, encryption that hinders content inspection, privacy regulations (GDPR/HIPAA) that limit monitoring, and the imitation of normal activities.

Detection relies on UEBA to establish baselines for user behaviors (e.g., alerting on 50GB downloads compared to a 5MB norm) through tracking of logins, access, and data movement; SIEM for correlating logs across platforms to identify irregular patterns; CASBs for flagging SaaS anomalies like unauthorized uploads; IAM audits to detect privilege creep; and AI for identifying low-and-slow multi-stage threats, with models adapting to new intelligence to maintain effectiveness.

Despite these advances, significant challenges persist in AI-based insider threat detection within clouds, including the need for continuous model retraining amid evolving threats, high false positive rates from legitimate behavioral variability, computational demands of deep learning in resource-scarce environments, and ethical concerns over privacy-invasive monitoring.

Fig .1: Figure

3. METHODOLOGY

The system employs a systematic, multi-phase approach for detecting insider threats using AI in cloud settings. Initially, it focuses on data collection, where a variety of user activity logs are compiled from cloud infrastructure. These logs encompass user login details, access records, file transfer logs, authentication information, API interactions, and network traffic data. The data is sourced from authorized individuals such as employees, administrators, contractors, and third-party vendors who engage with cloud resources. Additionally, logs are gathered from various cloud components, including virtual machines, storage systems, applications, and databases. This extensive data collection ensures that both user-level and system-level activities are captured for thorough threat analysis.

Once data is collected, the raw logs undergo preprocessing to enhance data quality and boost model performance. Given that cloud environments produce vast amounts of diverse and unstructured data, preprocessing techniques are employed to filter out noise, remove redundant entries, and standardize data formats. Log records are converted into structured and analyzable formats to ensure compatibility with machine learning algorithms. Feature extraction methods are applied to identify pertinent attributes, such as login frequency, access time patterns, data transfer volume, and access location. This step enhances detection efficiency and reduces computational complexity.

The third phase involves selecting and implementing suitable AI models for insider threat detection. The AI engine employs a mix of supervised, unsupervised, and deep learning techniques. Supervised learning algorithms like Random Forest and Support Vector Machines (SVM) are used to classify user activities based on labeled historical data. Deep learning models, such as Long Short-Term Memory (LSTM) networks and neural networks, are utilized to analyze sequential and complex behavioral patterns. Additionally, unsupervised anomaly detection techniques, including clustering and outlier detection algorithms, identify deviations from normal user behavior without needing predefined labels. The combination of these models enhances detection accuracy and adaptability.

During the model training phase, historical datasets containing labeled instances of normal and malicious activities are used to train the AI models. The system learns baseline user behavior patterns and distinguishes them from suspicious activities indicative of insider threats. Threat intelligence data and past incident records further bolster the learning process. Continuous retraining and model updates are conducted to incorporate new behavioral patterns and evolving attack strategies, ensuring long-term adaptability and improved detection performance.

Finally, in the detection phase, the trained AI models analyze incoming user activity data in real time. The system assesses behavioral deviations and assigns risk scores based on predefined thresholds. If an anomaly surpasses the risk threshold, it is classified as a potential insider threat. The system then generates alerts for security administrators, enabling timely investigation and response. In advanced implementations, automated mitigation actions such as account suspension, access restriction, or system isolation may be triggered to minimize damage and enhance overall cloud security.

4. PROPOSED ARCHITECHTURE

The suggested framework for AI-driven detection of insider threats in cloud settings is crafted to consistently oversee user actions, scrutinize behavioral trends, and identify harmful activities instantly. Given the ever-changing and dispersed nature of cloud infrastructure, the system employs a well-organized and expandable pipeline made up of six key components: User Layer, Cloud Infrastructure, Log Collection Module, AI Engine, Threat Detection Module, and Alert System. These elements collaborate to deliver comprehensive security monitoring and proactive threat prevention.

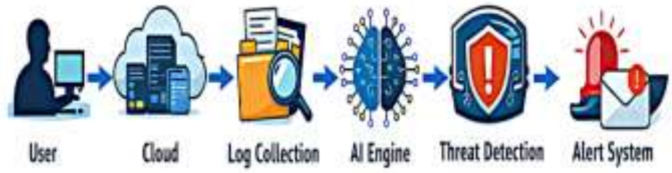

Fig .2: Figure

The architecture initiates with the User Layer, encompassing employees, administrators, contractors, or external vendors who utilize cloud resources. Since insider threats stem from authorized users with valid credentials, observing their behavior is essential. Users engage with cloud services for data storage, application usage, database management, and system configuration. Each user action generates activity logs, which are the primary data source for threat analysis.

The Cloud Infrastructure layer accommodates virtual machines, storage systems, applications, containers, and databases. Leading cloud service providers like Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform produce extensive operational logs, including authentication records, file access history, network traffic details, API calls, and system events. These logs offer crucial insights for detecting unusual access patterns or suspicious activities that might signal insider threats.

The Log Collection Module gathers logs from various cloud components in real time. It collects authentication logs, access control records, network activity logs, and system-generated events. As cloud environments generate large volumes of diverse data, preprocessing techniques such as data normalization, filtering, and feature extraction are employed to transform raw logs into structured and analyzable formats. This preprocessing step enhances model efficiency and ensures compatibility with machine learning algorithms.

The AI Engine serves as the core intelligence component of the proposed architecture. It examines user behavior using machine learning and deep learning techniques to spot anomalies and suspicious patterns. Behavioral analysis and pattern recognition mechanisms are used to establish baseline user activity profiles. Unsupervised learning methods, like clustering and anomaly detection algorithms, identify deviations from normal behavior without needing labeled datasets. Additionally, supervised learning models classify activities as benign or malicious based on historical attack data. The AI engine continuously updates its learning models to adapt to evolving insider threat strategies, thereby improving detection accuracy over time.

Once anomalies are identified, the Threat Detection Module assesses their severity and potential impact. This module correlates detected anomalies with historical attack patterns and threat intelligence data to determine whether the activity represents a genuine insider threat. A risk score is generated based on predefined thresholds, and activities exceeding the threshold are classified as high-risk incidents requiring immediate attention.

The final component of the architecture is the Alert System, which provides real-time notification to security administrators. Alerts may be delivered through email notifications, SMS messages, or centralized security dashboards. In advanced implementations, automated response mechanisms can temporarily suspend suspicious user accounts, restrict resource access, enforce multi-factor authentication, or isolate compromised systems. These actions help reduce potential damage and enable rapid response.

5. CONCLUSION

The incorporation of AI into cloud security marks a significant leap forward in identifying and addressing insider threats, which have become more complex and difficult to manage due to the legitimate access of authorized users. AI-powered systems utilizing machine learning, deep learning, anomaly detection, and real-time analytics greatly improve detection accuracy (up to 95%), decrease false positives by 20-30%, and facilitate swift automated actions like account isolation. This leads to enhanced cloud security across industries such as healthcare, finance, and e-commerce, while reducing detection times, operational expenses, and damage periods compared to traditional systems.

The suggested AI-based framework is scalable, robust, and mindful of privacy, featuring real-time log collection, behavioral analysis, threat assessment, and automated responses, along with explainable AI and privacy-preserving methods to ensure transparency and adherence to regulations. Despite challenges like computational requirements, data privacy, model bias, and the quality of training data, human oversight and ethical governance are vital for the responsible deployment of AI. Future developments include improving model efficiency, implementing federated learning, and incorporating advanced approaches like reinforcement learning and zero-trust security.

Ultimately, AI-driven detection of insider threats is crucial not merely a minor enhancement for contemporary cloud security. Organizations must prioritize intelligent, adaptive, and automated AI solutions in their cloud strategies to build resilient defenses, maintain operational continuity, and support secure digital transformation in an increasingly interconnected and threat-laden environment.

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