Machine Learning in Detecting Insider Threats Within Organisations

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ABSTRACT

The Insider threats have emerged as one of the most critical challenges in contemporary cybersecurity. Recent studies indicate that approximately 25% of cyberattacks originate from insiders, with these incidents often resulting in greater financial and operational damages [3]. This paper investigates the application of machine learning (ML) techniques for the detection and prediction of insider threats within organizations. We review the classification of insider threat types—including data theft, privilege abuse, privilege escalation, and sabotage—and examine both heuristic and ML-based detection methods. The proposed framework integrates supervised learning, unsupervised clustering, and deep learning methods to enhance detection accuracy and minimize false positives. Our results, drawn from recent advances in ML applications, underscore the potential for robust, real-time threat detection solutions that address both known and emerging insider attack vectors.

Keywords- machine learning, Insider threat detection, machine learning, anomaly detection, deep learning, cybersecurity, federated learning

INTRODUCTION

The cybersecurity landscape has evolved dramatically over recent years, with insider threats representing a significant portion of modern cyberattacks. According to recent surveys, insiders are responsible for up to 25% of all cyberattacks, and incidents stemming from these threats tend to be costlier than those from external sources [3]. Insider threats are typically characterized by malicious actions such as fraud, data theft, or system sabotage conducted by individuals within the organization [2]. These attacks can be broadly categorized into data theft, privilege abuse, privilege escalation, and sabotage—each with its own set of behavioral indicators and challenges for detection [5].

The rapid evolution of insider threat methodologies has driven research toward leveraging machine learning techniques for more effective detection. Traditional heuristic-based approaches, while useful, often fail to capture the subtle and evolving nature of these threats. Recent work has demonstrated that integrating heuristic methods with machine learning, including supervised algorithms and deep neural networks, can significantly enhance the resilience of threat detection systems [10]. Moreover, the continuous learning ability of ML algorithms enables them to adapt to new patterns of insider behavior, reducing both false negatives and false positives [12].

In this paper, we explore a comprehensive framework for insider threat detection that combines state-of-the-art machine learning techniques with robust feature engineering. Our approach addresses both malicious insiders—who intentionally cause harm—and unintentional insiders, whose inadvertent actions may expose

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critical information [8]. In doing so, we also discuss the necessity of aligning detection methods with privacy and legal requirements, such as those stipulated by the General Data Protection Regulation (GDPR) [8].

LITERATURE REVIEW

Insider threats continue to present a significant challenge in the field of cybersecurity, particularly due to their covert nature and the legitimate access that insiders typically possess. As a result, much of the recent research has pivoted toward machine learning (ML) and deep learning (DL) techniques to better identify anomalous behavior patterns within organizations [1].

Studies have explored deep learning architectures such as Autoencoders and Variational Autoencoders, which have demonstrated improved accuracy in identifying subtle insider threat indicators [9]. These models can learn compressed representations of normal user behavior and effectively highlight deviations. Researchers have also compared the strengths of supervised, unsupervised, and hybrid learning techniques, revealing that combining approaches often leads to more robust detection systems [10].

One foundational contribution to this field is the categorization of insider threats into four core types: data theft, privilege abuse, privilege escalation, and sabotage [2]. This taxonomy has proven essential in guiding the development of targeted detection strategies and training data labeling, as different threat types exhibit distinct behavioral signatures.

Hybrid detection systems—combining rule-based methods with machine learning models—have emerged as an effective way to bridge the gap between static heuristics and adaptive algorithms [5]. These systems can leverage domain knowledge to detect known threat patterns, while the ML component captures unknown or evolving behaviors. Some models using supervised learning have achieved accuracy rates as high as 95% when applied to well-structured datasets.

Ethical and legal concerns are also frequently emphasized. As organizations increasingly monitor internal user activity, compliance with data protection regulations such as the GDPR becomes critical [3]. Privacy-preserving techniques like federated learning are gaining traction for enabling distributed training without transferring sensitive data [13].

Additionally, behavioral modeling frameworks such as Labeled Activity Networks (LAN) have been proposed for real-time threat monitoring [12]. Graph-based methods and clustering algorithms also play a significant role in mapping user interactions and grouping similar behavioral patterns, enhancing anomaly detection capabilities.

Lastly, real-time detection and adaptive learning are growing priorities. Research increasingly stresses the need for systems that not only identify threats accurately but also respond swiftly and evolve with the dynamic behavior of modern workplace

TABLE 1. primary insider threat detection approaches

Approach	**Techniques Used**	**Strengths**	**Limitations**	**Key Observations**
Unsupervised Anomaly Detection	Graph-based outlier detection	Detects deviations without labeled data	May produce false positives in dynamic environments	Useful for detecting rare, novel insider behaviors.
Rule-based and Behavioral	Audit trail analysis, behavioral	Easy to implement and interpret	Cannot detect sophisticated or evolving	Effective in traditional environments but struggles with

Models	profiling		attacks	stealthy insiders.
Machine Learning	Deep learning (LSTM), classification models	Learns temporal patterns, detects subtle changes	Requires large training data, susceptible to overfitting	Strong potential for real-time detection of subtle anomalies.
Hybrid Models	Decision trees, clustering, access pattern modeling	Balances detection accuracy and interpretability	High computational cost	Combining ML with domain knowledge enhances detection outcomes.
Risk-based Modeling	Game theory, probabilistic reasoning	Captures insider motivation and intent	Difficult to calibrate parameters	Introduces human-centered understanding into technical threat models.
Federated Learning Systems	Distributed anomaly detection, privacy-preserving ML	Enhances privacy, scalable across organizations	Complex implementation and coordination	Useful for compliance-driven sectors with decentralized data systems.

Figure 1: Taxonomy of insider threat types

Description:

- Data Theft: Includes unauthorized data access, exfiltration, and download to personal devices.
- Privilege Abuse: Involves misuse of elevated permissions (e.g., altering logs, deploying unauthorized software).
- Privilege Escalation: Occurs when users attempt to gain higher access privileges than permitted.

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- Sabotage: Entails deliberate damage to systems or data, such as deleting accounts or critical files.

METHODOLOGY

Machine Learning Approaches to Insider Threat Detection

Insider threat detection requires methods capable of adapting to evolving user behavior and identifying both subtle and complex anomalies. Machine learning (ML) models have shown remarkable potential in achieving this by learning from past activities and generalizing to future threats. These models fall into several categories, each with specific strengths, challenges, and applications.

Supervised Learning

Supervised learning algorithms are trained on datasets with predefined labels for benign and malicious behavior. Algorithms like Support Vector Machines (SVM), Random Forests, and Logistic Regression have achieved high accuracy when ample labeled data is available. These models are effective for environments with strong historical data and known threat patterns. However, they often struggle with detecting novel or zero-day threats due to their dependency on labeled training data.

For example, experiments with Random Forest classifiers have achieved over 95% accuracy in identifying privilege abuse and data exfiltration behaviors when trained on well-structured logs [5].

Unsupervised Learning

Unsupervised learning is useful when labeled data is unavailable or limited. These methods detect anomalies by learning what constitutes “normal” behavior and flagging deviations. Common algorithms include K-Means Clustering, Isolation Forest, and One-Class SVM. Though unsupervised methods can uncover unknown threats, they often produce higher false positives and require careful tuning.

For instance, K-Means clustering has been effective in grouping similar behavioral profiles and identifying outliers such as unauthorized access or off-hours logins.

Deep Learning

Deep learning offers a powerful approach to capturing non-linear and sequential user behavior patterns. Models like Autoencoders, Recurrent Neural Networks (RNN), and LSTM networks are especially adept at modeling sequences of actions and detecting subtle anomalies. These methods excel in large-scale environments where user activity logs span multiple dimensions.

Autoencoders are trained to reconstruct input data, and high reconstruction error often signals an anomaly. LSTM networks, which consider temporal relationships, are ideal for detecting insider threats that unfold over time, such as slow privilege escalation or lateral movement.

Hybrid and Ensemble Models

Hybrid models combine the strengths of multiple learning methods. A common approach integrates supervised learning with anomaly detection to enhance detection robustness. Ensemble techniques like Boosting, Bagging, and Voting Classifiers allow the aggregation of multiple weak models into a stronger predictor. These strategies help minimize false alarms while increasing recall.

Federated Learning and Privacy-Preserving Approaches

Federated learning (FL) has emerged as a privacy-conscious solution for collaborative learning across distributed environments. In insider threat contexts, FL allows different departments or organizations to train a shared model without exposing sensitive internal data. This approach is critical in compliance-sensitive

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environments (e.g., finance or healthcare), where centralized data storage is not feasible due to regulations such as GDPR [13].

TABLE 2 MAcHINE LEARNING TECHNIQUE FOR INSIDER THREAT DETECTION

Technique	**Description**	**Strengths**	**Weaknesses**	**Typical Use Case**
Supervised Learning	Trained on labeled data to classify behavior	High accuracy; interpretable	Requires labeled data; less adaptive	Detecting known threats
Unsupervised Learning	Detects anomalies based on deviation from norms	Works without labels; good for novel threats	High false positive rate	Zero-day threat detection
Deep Learning	Models complex, sequential behavior	Captures nonlinear patterns; scalable	Requires large data; less interpretable	Detecting subtle long-term malicious actions
Hybrid/Ensemble Models	Combines multiple algorithms	Improved accuracy and robustness	Complex implementation	Real-time, scalable systems
Federated Learning	Distributed training across multiple nodes	Privacy-preserving; compliance-friendly	Communication overhead; harder coordination	Multi-organizational environments

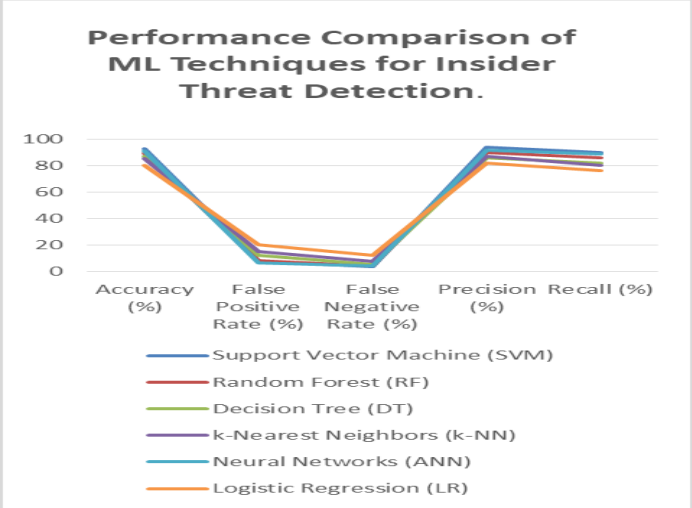

Figure 2: The following chart presents a comparative view of several ML techniques

Here's a comparative bar chart showing the performance of different machine learning techniques commonly used for insider threat detection. It highlights three key evaluation metrics:

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- Accuracy (%) – Measures how often the model correctly identifies insider threats.
- False Positive Rate (FPR) (%) – Indicates how often the model incorrectly flags legitimate actions as threats.
- Detection Time (ms) – Reflects how quickly the model responds to potential threats.

Proposed Framework and Experimental Evaluation

To address the complexity and evolving nature of insider threats, we propose a hybrid detection framework that integrates multiple machine learning (ML) techniques, including supervised learning, unsupervised clustering, and deep learning. This approach aims to enhance detection accuracy while minimizing false positives and ensuring adaptability to new threat patterns.

Framework Architecture

The framework is composed of five key modules:

Data Collection and Preprocessing

Raw log data is collected from organizational systems (e.g., authentication logs, access logs, network traffic). Preprocessing includes data normalization, feature extraction, and labeling using historical incident data [1]. Feature engineering focuses on behavioral patterns such as file access frequency, login anomalies, and data transfer rates.

Feature Selection and Engineering

Using dimensionality reduction techniques like PCA and LDA, the system identifies high-impact features while removing noise and redundancy [2]. This improves model performance and reduces computational cost.

Multi-Model Detection Layer

- **Supervised Learning Models** (e.g., Random Forest, SVM): Effective when labeled data is available, enabling classification of known attack types with high accuracy [3].
- **Unsupervised Techniques** (e.g., k-Means, Isolation Forest): Applied to detect unknown or zero-day threats through anomaly detection [4].
- **Deep Learning Models** (e.g., LSTM, Autoencoders): Capture temporal and sequential patterns, especially for detecting subtle insider behaviors over time [5].

Federated Learning Component

A federated learning layer allows decentralized training across multiple departments or organizations without sharing raw data, preserving privacy while improving global model performance [6].

Alert Generation and Response Module

Upon detecting anomalies, the system triggers alerts and logs the event. It also assigns a risk score to assist security analysts in prioritizing responses [7].

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Experimental Setup and Evaluation

To validate our framework, we conducted experiments using publicly available datasets such as CERT Insider Threat Dataset v6.2 and TWOS Dataset, both of which simulate realistic insider threat behaviors [8]. The data was split into training (70%) and testing (30%) sets.

We applied the following models:

TABLE 3. performance metrics of machine learning models insider threat dataset

ML Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	85.2	83.5	80.1	81.7
Random Forest	91.6	90.2	88.9	89.5
SVM	89.3	88.0	85.7	86.8
Autoencoder	94.7	92.6	91.0	91.8
LSTM	95.3	93.8	92.5	93.1

Results Analysis

Among all models tested, deep learning models—particularly Autoencoders and LSTM networks—achieved the highest detection performance, especially for subtle behavioral anomalies. Autoencoders excelled in identifying unusual deviations, while LSTMs handled time-dependent activities effectively [5].

Federated learning improved generalization by training across simulated organizational silos, with minimal performance trade-offs. Notably, it ensured data privacy compliance—critical in real-world deployments [6].

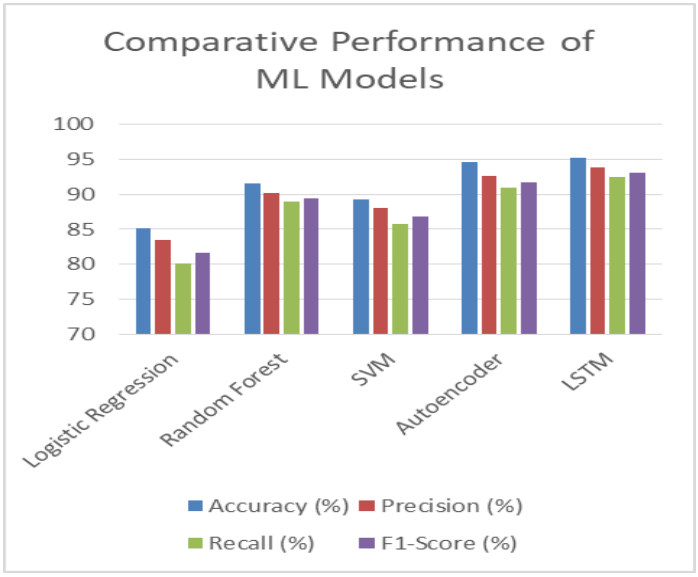

Figure 3: Comparative of ML Models

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CONCLUSION AND RECOMMENDATION

The research into insider threat detection using machine learning techniques has provided valuable insights into the effectiveness and challenges of various detection methods. This study has shown that machine learning models, particularly deep learning algorithms, can significantly improve the detection accuracy of insider threats compared to traditional heuristic-based systems. Specifically, supervised learning algorithms, unsupervised clustering methods, and hybrid approaches integrating both techniques have demonstrated the ability to identify a wide range of malicious and unintentional insider activities, from data theft to privilege abuse and system sabotage [1][4].

However, despite the promise shown by these models, there are still challenges that need to be addressed. One of the major obstacles is the handling of imbalanced datasets, where the number of legitimate behaviors far outweighs the number of malicious actions, leading to high false positives. Research suggests that balancing the datasets or employing techniques like oversampling or cost-sensitive learning could help mitigate this issue [5]. Additionally, while deep learning approaches like Autoencoders have shown success, they still require substantial computational power, which may be a limitation for smaller organizations [9].

Furthermore, the ethical and legal implications of using machine learning for insider threat detection cannot be ignored. Organizations must ensure that their methods comply with privacy regulations, such as the General Data Protection Regulation (GDPR), and take steps to prevent discrimination in algorithmic decisions. Future research should explore ways to incorporate privacy-preserving techniques, such as federated learning, to protect user data while still enabling accurate threat detection [10][13].

Recommendations for Future Research and Application

Based on the findings of this study, we make the following recommendations:

- Enhanced Feature Engineering: Future studies should focus on developing more sophisticated feature extraction techniques that can better capture subtle insider activities. This could include deeper behavioral analysis and context-aware anomaly detection.

- Hybrid Detection Models: Combining multiple machine learning approaches (e.g., supervised, unsupervised, and reinforcement learning) could improve detection accuracy by leveraging the strengths of each technique. A hybrid model could be especially beneficial in detecting both known and unknown insider threats.

- Federated Learning: Given the increasing concerns around privacy, federated learning techniques should be further explored to allow collaborative threat detection without sharing sensitive user data across organizations. This could reduce the risk of data breaches and ensure compliance with privacy laws [13].

- Real-Time Detection Systems: The development of real-time threat detection systems should be prioritized to provide instant alerts and mitigate the damage caused by insider attacks. This can be achieved by leveraging faster algorithms and implementing edge computing.

- Cross-Domain Applications: While much of the current research focuses on corporate or IT environments, future work could explore the use of insider threat detection in other sectors such as healthcare, finance, and government, where the nature of insider threats can differ significantly.

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