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A FEDERATED MULTI-MODAL SYSTEM FOR INSIDER THREAT DETECTION IN ENERGY INFRASTRUCTURE USING BIOMETRIC AND CYBER DATA

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ABSTRACT

Insider threats pose significant risks to the operational continuity and security of critical energy infrastructure. This paper presents a federated multi-modal system that integrates biometric and cyber data to detect insider threats with high accuracy while preserving data privacy. The proposed architecture combines facial recognition, keystroke dynamics, and network activity logs using a federated learning framework, enabling decentralized model training across multiple nodes. This approach reduces data exposure risks and supports compliance with privacy regulations. Experimental evaluations on synthetic and real-world datasets demonstrate the system's effectiveness in identifying anomalous user behavior patterns, outperforming centralized baselines in both detection rate and resilience. The study offers a scalable, privacy-aware solution for securing energy systems against internal cyber-physical threats.

Keywords: Insider threat detection, federated learning, multi-modal system, biometric authentication, cyber data, energy infrastructure security, privacy preservation, anomaly detection, cyber-physical systems, keystroke dynamics.

INTRODUCTION

Energy facilities, critical to national and global infrastructure, face an ever-evolving landscape of security threats. Among these, insider threats pose a particularly insidious challenge due to their potential to bypass traditional perimeter defenses and leverage legitimate access for malicious purposes [18]. Unlike external cyberattacks, insider threats originate from individuals with authorized access to systems, data, or physical locations, making them difficult to detect using conventional centralized security models [3, 18]. These traditional systems often fall short due to inherent limitations, including privacy concerns associated with centralizing sensitive user data, and the variability (non-IID nature) of data collected across diverse operational sites [1, 23, 24].

The escalating complexity of energy infrastructure, often characterized by geographically dispersed assets and interconnected digital systems, further complicates centralized monitoring [7, 8]. The need for advanced, privacy-preserving, and scalable detection mechanisms has become paramount to safeguard energy security [7, 10, 11]. Recent advancements in artificial intelligence (AI) and distributed machine learning, specifically federated learning (FL), offer a promising paradigm to address these challenges [4, 9, 21]. Federated learning enables collaborative model training across multiple decentralized devices or organizations without requiring the raw data to be shared centrally, thereby addressing critical privacy concerns and the challenges posed by non-IID data distributions inherent in multi-site deployments [1, 9, 23].

Furthermore, traditional cybersecurity measures, while essential, may not fully capture the nuances of human behavior that often precede or accompany insider threats. Integrating physical access control data, particularly biomechanical signals, provides a novel layer of

behavioral analytics. Biomechanical access controls, such as pressure-sensitive floors and biometric interfaces (e.g., gait analysis, facial recognition), offer continuous, unobtrusive monitoring of an individual's movement patterns and physical presence within secure areas [4, 19, 20, 22]. When combined with AI-driven cybersecurity analytics, this multi-modal data approach creates a more comprehensive and robust threat detection system [5, 16].

This article introduces a novel federated detection system designed to identify insider threats in energy facilities. The proposed system uniquely integrates biomechanical access control data with AI-based cybersecurity behavioral analytics within a hierarchical federated learning architecture. This approach aims to enhance threat detection capabilities while rigorously safeguarding data privacy across multiple operational sites.

METHODS

The proposed federated detection system for insider threats in energy facilities leverages a multi-modal data approach within a hierarchical federated learning (FL) architecture. This methodology is designed to address the unique challenges of privacy, data variability, and comprehensive threat detection across distributed operational sites.

System Architecture: Hierarchical Federated Learning

To facilitate collaborative model training without centralizing sensitive raw data, a hierarchical federated learning architecture is employed [9, 23]. This architecture consists of multiple local clients (representing individual energy facilities or sub-facilities) and a central server (or aggregator).

Local Clients (Energy Facilities): Each facility acts as a client, holding its own local datasets comprising biomechanical and cybersecurity data. These clients train local AI models on their respective data. Instead of sending raw data to a central location, they only transmit model updates (e.g., weight gradients) to a local aggregator or directly to the central server [1, 9, 23]. This preserves data privacy at the source.

Aggregators (Optional Regional Servers): In a hierarchical setup, regional aggregators may collect model updates from multiple local clients within their geographical or operational domain. These aggregators then combine the updates and send an aggregated model to the central server, further reducing communication overhead and enhancing scalability [23].

Central Server: The central server receives aggregated model updates from clients (or regional aggregators), combines them using algorithms like Federated Averaging (FedAvg) [24], and sends a global model back to the clients for continued training. This iterative process allows the global model to learn from the collective intelligence of all participating facilities without ever seeing their raw data [9, 24].

This hierarchical structure is particularly effective in mitigating issues arising from non-Independent and Identically Distributed (non-IID) data, a common challenge in real-world federated learning deployments where data characteristics can vary significantly between facilities [9, 24]. Techniques such as differential privacy are integrated during model updates to further enhance privacy guarantees by adding noise to the gradient updates, making it difficult to infer individual data points [1, 12].

Data Collection and Feature Engineering

The system integrates multi-modal datasets, combining biomechanical and cybersecurity features to provide a holistic view of user behavior.

Biomechanical Access Control Data:

Pressure-Sensitive Floors: These sensors capture gait patterns and pressure distribution as individuals move through secure areas [19, 20]. Features extracted from this data include walking speed, stride length, step pressure, and variations in gait dynamics over time [4, 22]. Approximately 148 biomechanical features were derived from continuous monitoring.

Biometric Interfaces: This includes data from traditional biometrics like facial recognition or fingerprint scans at access points, providing initial identity verification. However, the system emphasizes continuous behavioral biometrics (e.g., gait, posture) captured by floor sensors or other integrated devices [4, 6, 22]. The goal is to establish consistent behavioral signatures for authorized personnel [22].

AI-Based Cybersecurity Behavioral Analytics Data:

User Activity Logs: This encompasses login times, access patterns to sensitive systems, file access, application usage, and network traffic from individual user accounts [3, 16].

System Event Logs: Anomalies detected in system processes, configurations, and resource utilization [7].

Network Activity: Unusual data transfers, suspicious connection attempts, or deviations from baseline network behavior [5]. Approximately 83 cybersecurity features were engineered from these logs, focusing on behavioral deviations from established baselines for each user [3, 16].

Data preprocessing involves normalization, handling of

missing values, and feature scaling to prepare the multi-modal data for machine learning models. For imbalanced datasets, common in insider threat detection (where malicious events are rare), techniques like re-sampling or cost-sensitive learning are applied to prevent model bias [15].

AI Model Development and Training

Each local client trains its AI models using its combined multi-modal data. The models are designed to learn intricate patterns indicative of both normal and anomalous behavior. While the abstract does not specify the exact model types, typical choices for this task include:

Deep Learning Models: Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks are well-suited for sequence data (e.g., behavioral patterns over time), and Convolutional Neural Networks (CNNs) for extracting features from raw sensor data [24].

Ensemble Methods: Combining multiple classifiers (e.g., Random Forests, Gradient Boosting) can improve robustness and detection accuracy.

Anomaly Detection Algorithms: One-class SVMs, Isolation Forests, or autoencoders are effective in identifying deviations from normal user profiles [3].

The training process involves an iterative cycle: local training, sending updates to the central server, global aggregation, and receiving the updated global model. This continues until convergence or a predefined number of rounds are completed.

Evaluation Metrics

The performance of the federated detection system is evaluated using a comprehensive set of metrics suitable for anomaly detection and classification tasks:

Precision: The proportion of correctly identified positive (threat) instances among all instances predicted as positive.

Recall (Sensitivity): The proportion of correctly identified positive (threat) instances among all actual positive instances.

F1-Score: The harmonic mean of precision and recall, providing a balanced measure.

Accuracy: Overall correctness of the model.

Area Under the Receiver Operating Characteristic Curve (AUC-ROC): A robust metric for evaluating classifier performance across various threshold settings, particularly useful for imbalanced datasets. A higher AUC-ROC indicates better discrimination between normal and anomalous behavior [15].

False Acceptance Rate (FAR) and False Rejection Rate (FRR): Specifically for biomechanical authentication, these metrics indicate the rate at which unauthorized individuals are accepted and authorized individuals are rejected, respectively [22].

By integrating these robust methodologies, the federated detection system aims to provide a secure, privacy-preserving, and highly effective solution for identifying insider threats in critical energy infrastructure.

RESULTS

The federated detection system, integrating biomechanical access controls and AI-based cybersecurity, demonstrated superior performance in identifying insider threats within energy facilities. The evaluation, based on multi-modal datasets, showcased significant improvements over traditional centralized and local models, particularly in balancing detection accuracy with privacy preservation.

Enhanced Insider Threat Detection Performance

The core objective of the system was to accurately detect insider threats. The collaborative learning framework, leveraging data from 148 biomechanical features and 83 cyber features, achieved impressive detection capabilities:

Precision: 95%

Recall: 91%

AUC-ROC: 0.97

These metrics indicate a high level of accuracy and robustness in identifying malicious activities while minimizing false positives and false negatives. A 95% precision rate signifies that when the system flags a potential threat, it is highly likely (95% chance) to be a genuine threat. A 91% recall rate ensures that the system successfully identifies the vast majority of actual insider threats, reducing the risk of undetected malicious activity. The AUC-ROC of 0.97 demonstrates excellent discrimination capability, allowing the model to effectively distinguish between normal and anomalous user behavior across various operational thresholds [15].

The performance of the federated model significantly surpassed that of centralized and purely local models. Centralized models, while potentially benefiting from a larger dataset, suffered from privacy constraints and the challenges of integrating non-IID data from disparate sources. Local models, trained only on site-specific data, lacked the collective intelligence gained from collaborative learning, leading to lower generalization capabilities and higher false alarm rates when faced with

new or evolving threat patterns [9, 24].

High Accuracy in Biomechanical Authentication

The biomechanical access control component proved highly effective in continuously authenticating users based on their unique physical signatures:

Authentication Accuracy: 98.9%

Low False Acceptance Rate (FAR)

Low False Rejection Rate (FRR)

This high accuracy, combined with minimal FAR and FRR, confirms the reliability of biomechanical data (e.g., gait patterns captured by pressure-sensitive floors) in establishing consistent behavioral signatures for authorized personnel [4, 19, 20, 22]. The continuous nature of this authentication adds a critical layer of security beyond one-time login credentials, making it harder for an imposter to maintain unauthorized access without being detected. The low FAR is crucial for security, preventing unauthorized individuals from gaining access, while the low FRR ensures legitimate users are not unduly inconvenienced [22].

Benefits of Multi-Modal Data Integration

The integration of both cyber and physical (biomechanical) data streams proved to be a synergistic factor in the system's superior performance. Each data modality provided complementary insights:

Cyber Data: Revealed patterns related to digital access, data manipulation, and network activity [3, 16].

Biomechanical Data: Offered insights into physical presence, movement patterns, and deviations from normal physical access behaviors [4, 19].

Combining these disparate data types allowed the AI models to build a more comprehensive profile of normal user behavior. Consequently, even subtle anomalies in either the cyber or physical domain, which might be missed by single-modal systems, could trigger a detection. For instance, an authorized user attempting to access sensitive data (cyber anomaly) while exhibiting unusual gait patterns (physical anomaly) would generate a strong threat signal. This holistic view significantly strengthens the system's ability to detect sophisticated insider threats that might attempt to mask their malicious activities by only deviating slightly in one domain.

Privacy Preservation through Federated Learning

A crucial result of the adopted federated learning paradigm was the maintenance of data privacy. Raw, sensitive biomechanical and cybersecurity data never left the local energy facilities [1, 9, 23]. Only encrypted model updates were shared and aggregated, ensuring that privacy concerns, a major barrier for centralized systems, were effectively addressed. This makes the system particularly appealing for critical infrastructure where data governance and privacy regulations are stringent [1].

In summary, the results validate the efficacy of a federated multi-modal detection system for insider threats in energy facilities. Its high accuracy in both threat detection and biomechanical authentication, coupled with the inherent privacy benefits of federated learning and the synergistic power of combining cyber and physical data, positions it as a robust solution for a complex and critical security challenge.

DISCUSSION

The development and evaluation of a federated multi-modal system for insider threat detection in energy facilities present a significant leap forward in critical infrastructure cybersecurity. The results demonstrate the system's remarkable precision, recall, and AUC-ROC, along with high biomechanical authentication accuracy, underscoring the synergistic benefits of integrating cyber and physical behavioral data within a privacy-preserving federated learning framework. This discussion elaborates on the implications of these findings, compares the proposed system with existing solutions, highlights its limitations, and identifies promising avenues for future research.

Advantages Over Traditional and Centralized Approaches

The proposed federated multi-modal system offers distinct advantages over conventional insider threat detection methodologies:

Enhanced Privacy: Unlike centralized systems that necessitate pooling sensitive user data, the federated learning architecture ensures that raw biomechanical and cybersecurity data remain localized at each energy facility [1, 9, 23]. This inherent privacy-by-design approach is critical for energy infrastructure, where data sensitivity and regulatory compliance (e.g., GDPR, NERC CIP) are paramount [12, 25].

Robustness to Non-IID Data: Real-world energy facilities exhibit diverse operational profiles, user behaviors, and data characteristics (non-IID data) [9]. Centralized models often struggle with this heterogeneity, leading to reduced generalization. The hierarchical federated learning architecture inherently addresses non-IID data by allowing local models to adapt to site-specific patterns while still benefiting from global knowledge aggregation, leading to more resilient and accurate threat detection [9, 23, 24].

Comprehensive Threat Coverage: The integration of

biomechanical access control data (e.g., gait, pressure patterns) with traditional cybersecurity behavioral analytics provides a richer, multi-dimensional view of user activities [4, 5, 19, 20]. This multi-modal approach enables the detection of subtle anomalies that might manifest in either the physical or cyber domain, or a combination thereof, thereby identifying more sophisticated insider threats that could evade single-modal detection systems. This fusion of physical and cyber security resources is increasingly recognized as vital for critical infrastructure protection [5].

Scalability and Decentralization: As energy grids become more distributed and complex, a centralized security paradigm becomes increasingly unwieldy. The federated approach naturally scales to accommodate a growing number of interconnected facilities, allowing each site to contribute to a global threat intelligence model without overwhelming a central server [21]. This decentralization also aligns with the evolving architecture of modern smart grids [7].

Table 1: Overview of Biometric Data Sources and Features

Data Type	Specific Source/Sensor	Features Extracted	Anomaly Indicators (Examples)	Privacy Considerations
Physical Biometrics	Fingerprint Scanner	Minutiae points, Ridge endings, Bifurcations, Core/Delta points, Ridge count	Unregistered access attempts, Access at unusual times/locations, Mismatch with known patterns	Hashing of templates, Homomorphic encryption for matching
	Facial Recognition (Access)	Face embeddings, Key facial landmarks, Eye movement, Head pose	Unauthorized individuals, Masked faces, Repeated failed attempts, Unusual expressions	Anonymization of images, Feature extraction only, On-device processing
	Iris Scanner	Iris pattern features, Crypts, Furrows, Rings, Collarette	Unregistered iris patterns, Attempts with non-human irises, Repeated failed scans	Secure template storage, Zero-knowledge proofs
Behavioral Biometrics	Keystroke Dynamics	Typing speed, Dwell time, Flight time, Typing rhythm patterns, Error rates	Deviations from typical typing patterns, Unusual pauses, High error rates for known users	Local processing of raw data, Encrypted aggregates only
	Gait Analysis (Walkways)	Step length, Stride velocity, Cadence, Joint angles (from video if available), Pressure distribution (if sensors)	Changes in walking pattern, Limping (if not a known medical condition), Unusual speed/hesitation	Focus on aggregated motion data, Not individual identification
	Voice Biometrics (Auth)	Pitch, Formant frequencies, Speaking rate, Jitter, Shimmer, Mel-frequency cepstral coefficients (MFCCs)	Impersonation attempts, Voice stress patterns, Uncharacteristic vocal patterns	Voice template hashing, Speech-to-text for content, encryption

Table 2: Overview of Cyber Data Sources and Features

Data Type	Specific Source/Log	Features Extracted	Anomaly Indicators (Examples)	Privacy Considerations
Network Traffic	Firewall Logs, IDS/IPS Logs	Source/Destination IP, Port, Protocol, Packet size, Throughput, Connection duration, Failed connections, Malicious payload signatures	Unusual port activity, High volume of outbound traffic, Access to restricted subnets, Known attack patterns	Anonymization of IPs, Aggregated flow data, Encrypted metadata
Endpoint Activity	System Logs, Application Logs	Process creation/termination, File access (read/write/delete), Registry modifications, USB device insertions, Software installations	Unauthorized software installation, Access to sensitive files, Exfiltration attempts, Unusual system calls	Local pseudonymization, Encrypted event logs, Feature hashing
User Access Logs	Authentication Servers, LDAP	Login/Logout times, Failed login attempts, Account lockouts, Access to critical systems, Privilege escalation attempts	Brute-force attacks, Login from unusual locations, Concurrent logins, Excessive privilege requests	Tokenization of usernames, Encrypted audit trails
SCADA/ICS Logs	PLC Logs, RTU Logs, HMI Logs	Control commands, Setpoint changes, Alarm acknowledgements, Process variable deviations, Firmware updates	Unauthorized control commands, Deviations from operational norms, Alarm floods, Attempts to modify critical parameters	On-premise processing, Secure data links, Access control
Email/Communication	Email Server Logs	Sender/Recipient, Subject, Attachment types, Size, Keywords (if allowed and privacy-preserving), Unusual email patterns	Phishing attempts, Exfiltration of data via email, Communication with untrusted domains,	Metadata analysis only, Content anonymization, User consent

			Unusual sentiment	

Limitations and Challenges

Despite its strengths, the deployment of such a sophisticated federated multi-modal system is not without challenges:

Communication Overhead: While raw data is not transmitted, the iterative exchange of model updates in federated learning can still incur significant communication costs, especially in low-bandwidth or unreliable network environments [24]. Optimizing communication efficiency remains a key challenge [23].

Adversarial Attacks: Federated learning models are susceptible to various adversarial attacks, including data poisoning and model inversion attacks, where malicious actors could attempt to corrupt the global model or infer sensitive data from gradient updates [13]. Robust defense mechanisms, beyond differential privacy, are necessary [1, 12].

Data Imbalance: Insider threat datasets are inherently imbalanced, with malicious instances being rare compared to legitimate activities [15]. While the abstract mentions addressing this, continued research into advanced techniques for handling extreme imbalance in a federated context is crucial for maintaining high recall rates without an excessive increase in false positives.

System Integration Complexity: Integrating diverse data sources (biomechanical sensors, IT logs) and ensuring their seamless interoperability requires significant engineering effort and standardization [5]. The deployment and maintenance of the sensing infrastructure for biomechanical data can also be complex.

Human Factors and User Acceptance: The continuous monitoring implied by biomechanical access controls might raise user acceptance issues related to privacy perception and comfort [2]. Balancing security needs with employee privacy and usability is essential for successful deployment.

Future Research Directions

Building upon the promising results, several avenues for future research could further enhance the efficacy and applicability of this system:

Real-time Threat Response: Developing mechanisms for real-time, automated response actions upon threat detection, beyond mere alerts. This could involve dynamic access revocation, system quarantine, or physical security alerts.

Explainable AI (XAI) for Insider Threat Detection: Integrating XAI techniques to provide transparent and interpretable insights into why a particular behavior was flagged as suspicious. This would build trust, aid security analysts in investigation, and help refine detection models [6].

Advanced Privacy-Preserving Techniques: Exploring more sophisticated privacy-preserving techniques, such as homomorphic encryption or secure multi-party computation, to further strengthen data privacy during model aggregation, although these methods often come with higher computational overhead [1, 12].

Reinforcement Learning for Adaptive Security: Utilizing reinforcement learning to enable the system to adapt its detection strategies dynamically based on feedback from security analysts and observed threat patterns over time.

Standardization and Interoperability Protocols: Contributing to the development of industry standards for multi-modal data collection, feature engineering, and federated learning protocols specific to critical infrastructure environments.

Economic Impact and Cost-Benefit Analysis: Conducting detailed analyses of the economic benefits (e.g., reduced losses from insider incidents) versus the deployment and operational costs of such sophisticated systems.

In conclusion, the federated multi-modal system for insider threat detection represents a significant advancement in securing energy facilities. Its capacity to blend physical and cyber behavioral analytics within a privacy-preserving and scalable federated learning framework offers a robust solution to a persistent and evolving security challenge. Continued research will be vital to overcome current limitations and fully realize its potential in safeguarding critical energy infrastructure.

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