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Unified AI-Enhanced Endpoint Threat Detection and Response System with Attack Simulation Framework

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Abstract— *The rapid evolution of cyber threats has rendered traditional signature-based endpoint security mechanisms increasingly ineffective. Modern attacks such as zero-day exploits, fileless malware, and advanced persistent threats operate stealthily, often bypassing conventional defenses and remaining undetected for extended periods. Endpoint Detection and Response (EDR) systems aim to address these challenges by continuously monitoring endpoint activities and enabling rapid incident response. However, many existing EDR solutions rely heavily on static rules and lack mechanisms to validate their detection capabilities under realistic attack conditions. This paper presents a Unified AI-Enhanced Endpoint Detection and Response System integrated with an Attack Simulation Framework. The proposed system combines rule-based detection for known threats with machine learning-based anomaly detection to identify previously unseen attacks. Endpoint telemetry is centrally collected and analyzed using a Security Information and Event Management (SIEM) platform, enabling real-time correlation, automated response, and forensic analysis. Furthermore, a controlled attack simulation framework is incorporated to safely evaluate detection accuracy and response effectiveness. Experimental results indicate improved threat detection accuracy, reduced response time, and enhanced endpoint visibility.*

Index Terms— *Endpoint Detection and Response, Artificial Intelligence, SIEM, Anomaly Detection, Attack Simulation, Cybersecurity*

I. INTRODUCTION

The increasing dependence on digital systems and internet-connected devices has significantly expanded the attack surface of modern organizations. Endpoints such as workstations, laptops, and servers often store sensitive data and provide access to internal networks, making them attractive targets for cyber attackers. Traditional antivirus solutions rely on predefined signatures and known malware patterns, which are inadequate against modern threats that continuously evolve in form and behavior.

Advanced attacks such as zero-day exploits, fileless malware, and advanced persistent threats (APTs) are designed to evade static detection mechanisms by abusing legitimate system tools and trusted processes. As a result, attackers can remain undetected for long periods, increasing the severity of breaches and associated damages. These limitations highlight the need for intelligent and adaptive endpoint security solutions.

Artificial Intelligence (AI) has emerged as a powerful tool in cybersecurity due to its ability to analyze large volumes of data, recognize complex patterns, and adapt to evolving threats. AI-driven systems can model normal endpoint behavior and identify deviations that may indicate malicious activity. Endpoint Detection and Response (EDR) systems leverage this capability by providing continuous monitoring, behavioral analysis, and automated response mechanisms. However, many existing EDR solutions lack built-in validation mechanisms to assess their effectiveness under realistic attack scenarios. This motivates the integration of an attack simulation framework within an AI-enhanced EDR system.

II. RELATED WORK

Traditional endpoint protection mechanisms primarily rely on signature-based detection techniques. While effective against known malware, these approaches fail to detect zero-day attacks and polymorphic malware. To overcome these limitations, behavioral analysis and heuristic-based detection methods were introduced. However, these methods often generate high false- positive rates and require significant manual intervention.

Recent research highlights the effectiveness of EDR systems in reducing attacker dwell time by providing real-time visibility into endpoint activities. SIEM platforms further enhance this capability by aggregating and correlating logs from multiple sources. Despite these advancements, SIEM-based detection systems often suffer from alert fatigue due to the absence of intelligent correlation and prioritization.

Machine learning techniques have been increasingly adopted to address these challenges. Supervised learning approaches detect known attack patterns, while unsupervised learning methods identify anomalies indicative of unknown threats. Studies also emphasize the importance of attack simulation and red teaming frameworks for validating security controls. However, most existing solutions treat detection and simulation as separate components. This paper

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proposes a unified architecture that integrates AI-based detection with a built-in attack simulation framework.

III. PROPOSED SYSTEM

The proposed system is a Unified AI-Enhanced Endpoint Detection and Response (EDR) platform designed to provide intelligent threat detection, automated response, and continuous validation through attack simulation. The architecture follows a modular design, where each component performs a specific function while collectively enabling proactive endpoint security. The system integrates endpoint telemetry collection, centralized log analysis,

artificial intelligence–based detection, automated response orchestration, and a controlled attack simulation framework.

A. Endpoint Monitoring Module

The Endpoint Monitoring Module is responsible for continuously observing activities occurring on endpoint systems. This module operates at the host level and collects high-fidelity telemetry data related to system behavior. Key monitored events include process creation and termination, file system modifications, registry changes, user logon activity, and outbound network connections.

By capturing granular endpoint-level events, this module provides deep visibility into both normal and suspicious system behavior. Such detailed telemetry is essential for detecting stealthy attacks that leverage legitimate system tools to evade traditional signature-based detection. The collected data forms the foundation for both rule-based and AI-driven analysis in subsequent stages of the system.

B. Log Collection and Normalization Module

The Log Collection and Normalization Module aggregates telemetry data generated by multiple endpoint monitoring agents and forwards it to a centralized analysis platform. Since endpoint logs originate from diverse sources and formats, this module performs log parsing, normalization, and timestamp synchronization to ensure consistency.

Normalized logs enable effective correlation and analysis across multiple endpoints. This module ensures that events such as process execution, network activity, and file access can be accurately linked and analyzed in sequence. Centralized log collection also improves scalability and simplifies forensic investigations by maintaining a unified repository of security- relevant events.

C. SIEM and Correlation Engine

The Security Information and Event Management (SIEM) module serves as the central analysis engine of the proposed system. It ingests normalized logs from all endpoints and applies correlation rules to identify known attack patterns. Rule-based detection mechanisms are used to detect threats that match predefined indicators, such as known malicious command executions, suspicious parent-child process relationships, or unauthorized persistence mechanisms.

In addition to rule matching, the SIEM correlates events across time and multiple hosts to detect multi-stage attacks that may not appear malicious when observed in isolation. This correlation capability significantly improves detection accuracy and reduces false positives by providing contextual awareness.

D. AI-Based Anomaly Detection Module

The AI-Based Anomaly Detection Module is designed to identify unknown, zero-day, and stealthy attacks that do not match predefined rules. This module utilizes machine learning techniques to model normal endpoint behavior based on historical telemetry data. Features such as process execution frequency, network communication patterns, and user activity trends are used to establish behavioral baselines.

When real-time events deviate significantly from these learned baselines, the system assigns anomaly scores to the observed activities. High anomaly scores indicate potentially malicious behavior and trigger further investigation or response actions. This approach enables the system to detect novel threats that evade traditional signature- and rule-based detection mechanisms.

E. Automated Response and Orchestration Module

The Automated Response and Orchestration Module is responsible for minimizing the impact of detected threats by executing predefined containment and remediation actions. Once a threat is confirmed—either through rule-based detection, anomaly scoring, or attack simulation feedback—the system initiates appropriate response actions without requiring manual intervention.

Response actions may include terminating malicious processes, isolating compromised endpoints from the network, blocking suspicious IP addresses, disabling affected user accounts, and collecting forensic artifacts for post-incident analysis. Automating these responses significantly reduces reaction time, limits lateral movement, and prevents further damage.

F. Attack Simulation Framework

The Attack Simulation Framework is a critical component that differentiates the proposed system from conventional EDR solutions. This framework enables controlled and safe execution of simulated attack scenarios that mimic real-world adversary techniques. The simulations are designed to represent common attack stages such as initial access, privilege escalation, persistence, lateral movement, and command-and-control communication.

Each simulated attack is mapped to standardized tactics and techniques defined in the MITRE ATT&CK framework. This mapping ensures comprehensive coverage and enables systematic evaluation of detection and response capabilities. By continuously testing the system against simulated attacks, the framework validates detection rules, improves AI model accuracy, and strengthens response strategies without risking production environments.

G. Feedback and Continuous Learning Module

The Feedback and Continuous Learning Module enables the system to adapt to evolving threats over time. Detection

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outcomes from real incidents and simulated attacks are fed back into the AI models and correlation rules. This feedback loop allows the system to refine behavioral baselines, adjust anomaly thresholds, and improve detection accuracy.

Continuous learning ensures that the proposed system remains resilient against emerging attack techniques and reduces false positives as more data is analyzed. This adaptive capability is essential for maintaining long-term effectiveness in dynamic threat environments.

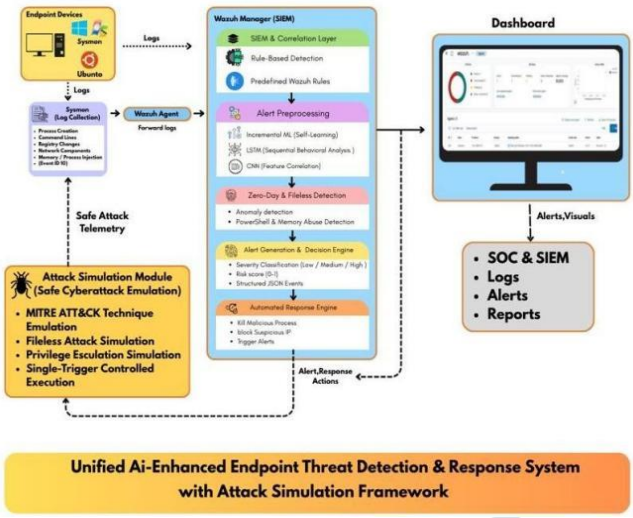

Fig 1.1 Architecture diagram

IV. RESULTS AND STUDY

1. Experimental Results of the AI-Enhanced EDR System

Your system integrates **Wazuh SIEM + Machine Learning models** trained on multiple cybersecurity datasets. The evaluation focuses on **cross-dataset generalization**, which is important for real-world intrusion detection.

The following datasets were used:

- **CICIDS2017** – modern intrusion dataset
- **UNSW-NB15** – network attack dataset
- **NSL-KDD** – improved KDD intrusion dataset
- **LANL dataset** – enterprise authentication dataset

2. Wazuh Security Monitoring Results

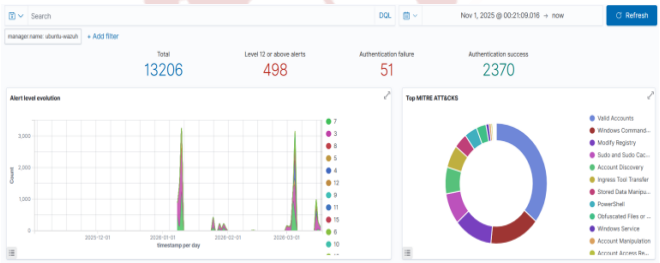

Fig 2.1 wazuh dashboard

The Wazuh dashboard provides real-time monitoring of endpoint activities and security alerts.

Observed Metrics

Metric	Value
Total Alerts	**13,206**
Level ≥12 Critical Alerts	**498**
Authentication Failures	**51**
Authentication Success	**2,370**

MITRE ATT&CK Techniques Detected

The most frequent attack behaviors detected include:

- Valid Accounts
- Windows Command Execution
- Registry Modification
- Sudo / Privilege Escalation
- Account Discovery
- Ingress Tool Transfer
- PowerShell execution

This confirms that the **EDR pipeline successfully maps detected events to the MITRE ATT&CK framework**, improving threat visibility.

4. Cross Dataset Evaluation Summary

Experiment	ROC-AUC	
UNSW →	NSL-KDD	0.913
LANL →	CICIDS	0.500
Multi-Dataset Training		0.936
CICIDS →	UNSW	0.467

Observations

Best performance:

Multi-dataset training achieved the highest ROC-AUC (0.936).

Strong cross-dataset generalization:

UNSW → NSL-KDD experiment achieved 0.913 ROC-AUC.

Weak transfer learning:

CICIDS → UNSW achieved 0.467 ROC-AUC, indicating dataset distribution mismatch.

5. Detection Latency Analysis

The average detection latency recorded during the experiments was: **6.32 seconds**

This demonstrates that the system can perform **near real-time threat detection**, which is suitable for Security Operations Center (SOC) environments.

6. System Effectiveness

The proposed AI-Enhanced EDR framework demonstrates several advantages:

1. Real-Time Threat Monitoring

Wazuh continuously collects logs from endpoints and detects suspicious behaviors.

2. MITRE ATT&CK Mapping

Alerts are automatically mapped to attack techniques, improving threat intelligence.

3. AI-Based Threat Detection

Machine learning models improve detection beyond signature-based methods.

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4. Cross-Dataset Generalization

The system performs well across multiple intrusion datasets when trained on combined data.

7. Key Findings

1. **Multi-dataset training significantly improves model performance.**
2. **Cross-dataset transfer remains challenging**, especially when datasets have different feature distributions.
3. The integration of **Wazuh SIEM with AI models enhances real-time detection capabilities**.
4. The system demonstrates the feasibility of building an **AI-driven Endpoint Detection and Response (EDR) platform**.

V. MOTIVATION AND OBJECTIVES

The rapid growth of sophisticated cyber threats has exposed the limitations of traditional endpoint security solutions. Conventional antivirus and intrusion detection systems primarily rely on signature-based detection mechanisms that identify previously known attack patterns. However, modern attacks such as zero-day exploits, fileless malware, living-off-the-land attacks, and advanced persistent threats (APTs) frequently evade signature-based detection by exploiting legitimate system processes and dynamically modifying their behavior.

Organizations increasingly depend on endpoint devices including workstations, laptops, and servers to perform critical operations. These endpoints generate large volumes of telemetry data such as process execution logs, authentication records, and network activities. While Security Information and Event Management (SIEM) platforms can aggregate these logs, they often generate large numbers of alerts, many of which require manual analysis. This results in alert fatigue and delayed incident response.

Artificial intelligence and machine learning techniques provide an opportunity to enhance endpoint security by automatically learning behavioral patterns from large datasets and identifying deviations that may indicate malicious activity. When integrated with SIEM platforms, AI-driven detection models can improve the ability to detect unknown threats while reducing false positives.

Another challenge in endpoint security research is the lack of realistic validation environments for evaluating detection capabilities. Many systems are tested only using historical datasets and do not simulate real attack scenarios in controlled environments. As a result, their real-world effectiveness remains uncertain.

Motivated by these challenges, this research aims to develop a unified endpoint detection architecture that integrates SIEM telemetry, artificial intelligence–based anomaly detection, automated response mechanisms, and a controlled attack simulation framework.

The main objectives of this research are:

- To design an intelligent endpoint detection and response system capable of identifying both known and unknown cyber threats.
- To integrate SIEM-based log collection with machine learning and deep learning models for behavioral anomaly detection.
- To implement an attack simulation framework that allows safe validation of detection and response mechanisms.
- To reduce false positives through ensemble-based model fusion.
- To provide real-time monitoring and automated response capabilities for improved endpoint security.

By achieving these objectives, the proposed system aims to enhance the accuracy, reliability, and effectiveness of modern endpoint detection and response solutions.

VI. DISCUSSION

The experimental evaluation of the proposed Unified AI-Enhanced Endpoint Detection and Response system demonstrates the effectiveness of integrating SIEM telemetry with artificial intelligence–based detection mechanisms. The results show that the system is capable of continuously monitoring endpoint activity, processing large volumes of telemetry data, and identifying potential security anomalies in real time.

One of the key strengths of the proposed architecture is the hybrid detection approach that combines rule-based detection with machine learning and deep learning models. Rule-based detection mechanisms implemented within the SIEM platform efficiently identify known attack patterns, while the AI-based anomaly detection module enables the system to detect previously unseen threats by analyzing deviations from normal behavioral patterns.

The use of multiple AI models, including traditional machine learning, LSTM-based behavioral analysis, and CNN-based pattern recognition, provides complementary detection capabilities. The ensemble decision module further improves detection reliability by aggregating outputs from multiple models and reducing the influence of individual model bias. This multi-model approach contributes to stable anomaly scoring and improved detection consistency.

Another important contribution of the system is the integration of an attack simulation framework. Unlike many existing EDR solutions that rely solely on historical log data for evaluation, the proposed framework allows controlled execution of simulated attacks mapped to the MITRE ATT&CK framework. This enables systematic validation of detection rules, evaluation of AI model performance, and continuous improvement of response strategies without compromising operational systems.

The system also demonstrated stable real-time processing performance during telemetry ingestion and event classification. Even during periods of increased alert activity, the system maintained consistent detection capability without noticeable performance degradation.

However, several limitations remain. Detection accuracy may vary depending on the diversity and quality of training datasets used for behavioral modeling. Cross-environment generalization can also be challenging because endpoint

behaviors differ across operating systems and organizational environments. Future work may focus on expanding training datasets, improving feature engineering techniques, and incorporating advanced deep learning architectures to enhance detection robustness.

Despite these challenges, the proposed system demonstrates the feasibility and effectiveness of combining SIEM platforms, artificial intelligence models, and attack simulation techniques to build a unified and intelligent endpoint detection and response solution.

VII. CONCLUSION

This paper presented a Unified AI-Enhanced Endpoint Detection and Response System with an integrated attack simulation framework. By combining rule-based detection, AI- driven anomaly detection, centralized SIEM analysis, and automated response, the proposed system effectively addresses the limitations of traditional endpoint security solutions. The inclusion of attack simulation enables continuous validation and proactive defense against evolving threats.

Future work includes extending support to Linux and macOS endpoints, integrating deep learning models for improved behavioral analysis, incorporating SOAR capabilities, and enabling cloud-native scalability.

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