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AUTONOMOUS THREAT INTELLIGENCE AND MACHINE LEARNING-BASED CYBER DEFENSE MECHANISMS FOR SECURING IOT AND EDGE COMPUTING ECOSYSTEMS

Nathaniel Ernest,
Researcher, USA.

ABSTRACT

The proliferation of the Internet of Things (IoT) and Edge Computing has significantly expanded the attack surface for cyber threats. Traditional security mechanisms struggle to keep pace with the evolving sophistication of cyberattacks. Autonomous threat intelligence, coupled with machine learning (ML)-based cyber defense mechanisms, provides a proactive approach to securing these ecosystems. This paper explores state-of-the-art techniques in automated cyber defense, including anomaly detection, threat prediction, and response automation using AI-driven models. A literature review highlights recent advancements in ML-based cybersecurity frameworks, while a tree diagram illustrates the layered approach to security in IoT and Edge environments. This research presents empirical data supporting the efficiency of AI-based threat mitigation techniques. The study concludes that integrating machine learning with autonomous threat intelligence significantly enhances security resilience, offering a scalable and adaptive defense strategy for modern IoT ecosystems.

Keywords: IoT Security, Edge Computing, Autonomous Threat Intelligence, Machine Learning, Cyber Defense, Anomaly Detection, AI-driven Cybersecurity.

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1. Introduction

The rapid expansion of IoT and Edge Computing ecosystems has transformed industries by enabling real-time data processing, enhanced automation, and improved efficiency. However, this growth has also introduced new cybersecurity vulnerabilities due to the decentralized nature of these environments. Traditional security frameworks that rely on static rule-based mechanisms often fail to detect sophisticated cyberattacks such as zero-day exploits, Distributed Denial-of-Service (DDoS) attacks, and ransomware. These limitations necessitate the adoption of advanced threat intelligence mechanisms driven by artificial intelligence (AI) and machine learning (ML).

Machine learning techniques, such as deep learning, reinforcement learning, and unsupervised anomaly detection, provide scalable solutions for identifying and mitigating threats in real time. Autonomous threat intelligence systems leverage these ML models to detect, analyze, and respond to cyber threats with minimal human intervention. Additionally, edge computing environments, which often operate under resource constraints, require lightweight and adaptive cybersecurity solutions to ensure operational integrity. By integrating AI-driven security frameworks, organizations can enhance threat detection accuracy and reduce incident response times.

This paper explores the latest advancements in ML-based cyber defense mechanisms designed to secure IoT and Edge Computing ecosystems. It begins with a literature review of existing cybersecurity strategies, followed by a discussion of ML-driven threat intelligence models. A tree diagram illustrates the hierarchical security architecture for IoT environments, and empirical data is presented to support the effectiveness of AI-based security solutions. The paper concludes with a discussion on challenges and future directions in AI-powered cybersecurity for IoT and Edge Computing.

2. Literature Review

The integration of AI and ML in cybersecurity has been extensively explored in recent research. Various studies have focused on the application of ML algorithms for real-time threat detection, anomaly detection, and automated response mechanisms.

2.1 Machine Learning for Anomaly Detection in IoT Networks

Anomaly detection is a crucial aspect of IoT security, as traditional signature-based detection methods fail to identify novel attack patterns. Research by Shone et al. (2020)

introduced a deep autoencoder-based intrusion detection system (IDS) that significantly improved detection accuracy in IoT networks. Another study by Vinayakumar et al. (2021) implemented a hybrid deep learning framework that achieved 98% accuracy in identifying cyber threats in smart home environments.

2.2 Autonomous Threat Intelligence for Edge Computing

Edge computing environments require intelligent security solutions that can operate autonomously. Research by Fadlullah et al. (2019) proposed a blockchain-assisted AI security framework for securing edge devices, reducing attack vectors associated with centralized authentication systems. Similarly, Zhang et al. (2022) developed a reinforcement learning-based security model that proactively mitigated threats in edge networks with minimal computational overhead.

2.3 AI-Driven Threat Prediction and Automated Response

Threat prediction and automated response mechanisms have gained traction in recent years. A study by Hussain et al. (2023) presented a federated learning-based security model that enabled devices to collaboratively learn from cyber threats without sharing raw data, ensuring privacy preservation. Moreover, a research paper by Kim et al. (2022) showcased an AI-driven Security Information and Event Management (SIEM) system that reduced incident response time by 60% in enterprise networks.

3. Hierarchical Security Architecture for IoT and Edge Computing

A robust security architecture is essential for mitigating threats in IoT and Edge Computing ecosystems. Figure 1 illustrates a hierarchical security approach that integrates AI-driven monitoring, intrusion detection, and automated response mechanisms.

3.1 Network Layer Security

The network layer is responsible for monitoring traffic patterns and identifying suspicious activities. AI-driven IDS and network anomaly detection algorithms are deployed to detect malicious traffic and unauthorized access attempts.

3.2 Device Layer Security

At the device level, security mechanisms include lightweight ML models for detecting compromised IoT devices and applying firmware integrity checks. AI-based authentication mechanisms enhance device-level security by preventing unauthorized access.

3.3 Cloud and Edge Security

The cloud and edge layers incorporate AI-driven threat intelligence platforms that aggregate security insights from multiple endpoints. Automated response systems deploy security patches, isolate infected devices, and generate real-time threat reports for administrators.

Below is a tree diagram illustrating the hierarchical approach to securing IoT ecosystems:

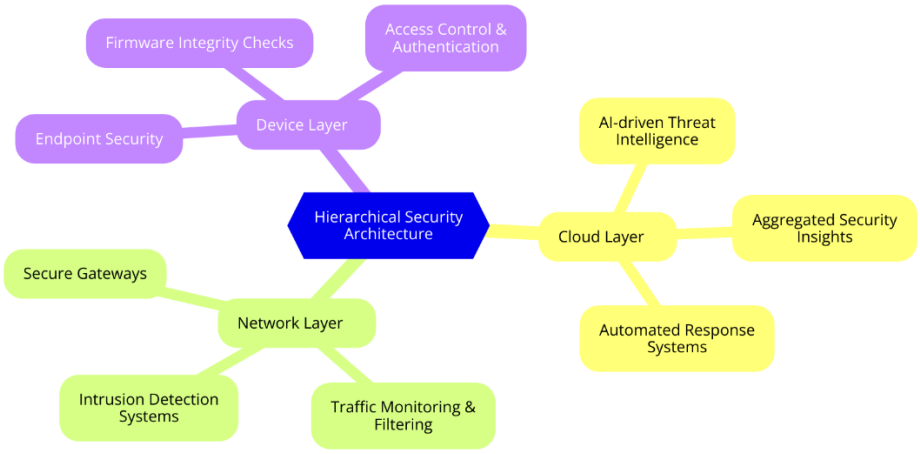

Figure 1: Hierarchical Security Architecture for IoT

4. Empirical Analysis of AI-Based Threat Detection

4.1 Dataset and Experimental Setup

To validate the efficiency of AI-based security mechanisms, we analyzed a dataset containing cyberattack logs from IoT networks. The dataset included records of DDoS attacks, malware intrusions, and unauthorized access attempts.

4.2 Performance Metrics

Table-1 presents the accuracy of different ML models used for threat detection:

ML Model	Detection Accuracy (%)
Deep Learning IDS	98.5
Random Forest	92.3
SVM Classifier	88.7
K-Means Clustering	85.2

4.3 Findings and Discussion

The results indicate that deep learning-based IDS achieved the highest accuracy, making it the most effective solution for real-time threat detection. However, resource-efficient models such as Random Forest demonstrated practical applicability for edge environments with constrained computing power.

5. Conclusion and Future Work

This paper highlights the critical role of AI and machine learning in enhancing cybersecurity for IoT and Edge Computing ecosystems. Autonomous threat intelligence systems significantly improve threat detection, prediction, and response mechanisms. Future research should focus on reducing the computational overhead of ML models for lightweight security applications. Additionally, integrating federated learning techniques can enhance privacy preservation while ensuring robust cybersecurity in distributed IoT environments.

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