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AI-Driven Real-Time Cybersecurity Model for Automated Threat Detection and Self-Patching

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ABSTRACT: The security landscape is changing constantly, traditional defensive measures like WAFs (Web Application Firewalls) and signature-based threat detection machine systems are not able to tackle sophisticated attacks. In this study we present a central AI model processed for real-time detection, prevention and autonomous patching of vulnerabilities without human interference. Utilizing Machine Learning (ML), Large Language Models (LLMs), and Reinforcement Learning (RL), the outlined model continuously monitors running applications for security vulnerabilities and deploys real-time remediation strategies. Our model does not rely on static rules as most traditional security tools do, but rather continuously adapts to new threats by observing patterns in the attack vectors. This approach significantly reduces the window of exploitation for attackers and minimizes system downtime. By integrating NLP-based vulnerability analysis, heuristic threat detection, and self-improving federated learning, our AI model redefines automated cybersecurity defenses.

Keywords: AI Model, ML, LLM, NLP, Reinforcement Learning, Cybersecurity, Real-Time Threat Detection, Self-Patching, Heuristic Security, Federated Learning.

INTRODUCTION

The digital environment is changing so fast that it has seen a surge in advanced cyber threats unlike anything before. The countermeasures (ie traditional security mechanisms such as Web Application Firewalls [WAFs] and signature-based Intrusion Detection Systems [IDS]) have become inadequate against continuously evolving attack strategies. These so-called conventional defenses mainly depend on static threat intelligence and preset rules, and are powerless against zero-day vulnerabilities, advanced persistent threats (APTs) and AI-based adversarial cyber-attacks. This contradiction between the changing threats and an out-of-date security solution demands a flexible and real-time security model that learns on its own. This study presents a cybersecurity framework powered by AI that not only detects threats but also eliminates them before any damage occurs. Functioning in real time, this system identifies vulnerabilities on its own, neutralizes threats, and automatically patches weaknesses without needing human involvement (Harris *et al.*, 2022). In contrast, traditional security tools respond after an event, depending on set signatures, manual updates, and slow reaction times, which is outdated. Cyber attackers can act quickly, taking advantage of weaknesses before patches become available. Our AI model changes the game by adopting a proactive approach; it continuously monitors system behaviour, anticipates possible attack pathways, and implements defences even before an exploit occurs. It utilizes Machine Learning (ML) to identify patterns of attack, Large Language Models (LLMs) for in-depth analysis of vulnerabilities, and Reinforcement Learning (RL) to adapt and enhance its defences over time. Unlike standard security measures that rely on reactive rules or human oversight, this AI develops independently. It analyses current threats, learns from worldwide attack patterns, and applies real-time solutions without downtime. The window of risk for exploitation significantly decreases. Through heuristic anomaly detection, federated learning for shared knowledge, and kernel-level surveillance for low-level systemic threats, this model revolutionizes cybersecurity from a passive shield into an active, self-improving defence. No delays. No manual patching waits times. Just an intelligent, continuously operational defence system that keeps digital infrastructure strong against cyber threats (Evans & Brown, 2021). Moreover, traditional vulnerability patching is a slow process requiring security teams to spend time evaluating vulnerabilities, developing solutions, and manually deploying patches. That task usually takes longer than the release time, leaving systems vulnerable to attack during this fall. We solve this by automating the entire vulnerability management lifecycle. Using NLP-based vulnerability assessment and heuristic-guided threat detection, the AI can identify code vulnerabilities, generate patches and deploy them in real-time without impacting operations. This does wonders for security, but it also reduces manual process overhead.

However, the use of AI in cybersecurity has brought about challenges including adversarial AI attacks, false positives, and the need for continuous learning. Still, with our model we provide fast responsive security via reinforcement learning, logical reasoning via symbolic AI, and kernel level monitoring for possible undetectable system inefficiencies we build a secure framework. It provides in-depth insight into the model architecture, approach, and practical application of this AI-driven cybersecurity solution and its potential to reshape current cyber protection paradigms (Wang *et al.*, 2019). In contrast, traditional security tools respond post-event, depending on outdated set signatures, manual updates, and slow response times. Criminals can take advantage of weaknesses in the time between a vulnerability is discovered and an update deployed.

RELATED WORK

Cybersecurity has evolved significantly with advancements in AI, machine learning, and automation. Traditional Intrusion Detection and Prevention Systems (IDS/IPS) monitor network traffic and system activities for malicious behavior. Signature-based IDS relies on predefined attack patterns, while anomaly-based IDS uses machine learning to detect deviations from normal behavior. However, these systems often require constant updates to remain effective (Smith *et al.*, 2020). Similarly, Web Application Firewalls (WAFs) are widely used to protect web applications from SQL injection and cross-site scripting (XSS) attacks, with modern WAFs integrating AI-driven analytics to improve detection accuracy (Johnson & Lee, 2021). Security Information and Event Management (SIEM) platforms have been developed to aggregate security data and apply analytics for threat detection, integrating AI to automate response mechanisms (Patel *et al.*, 2022). Endpoint Detection and Response (EDR) solutions enhance device-level security by using behavior analysis to detect malware and zero-day exploits, even when attack patterns are unknown (Gupta & Zhang, 2023). Threat Intelligence Platforms, which compile global cyber threat data, have been instrumental in identifying and mitigating security risks in real time (Wang *et al.*, 2019). AI has further advanced cybersecurity through machine learning-based anomaly detection, where deep learning and statistical models analyze network traffic and user behavior to detect irregular activities (Chen & Davis, 2021). Reinforcement learning (RL) has also been explored to develop adaptive security strategies that optimize defenses in response to evolving threats (Miller *et al.*, 2020). Another major innovation is federated learning, which allows organizations to share intelligence and train AI models without exposing sensitive data, improving collective cybersecurity (Rodriguez & Kim, 2022). With adversarial AI threats growing, research has focused on Adversarial Machine Learning (AML) defenses, which train models to resist manipulation (Thompson *et al.*, 2023). Additionally, Natural Language Processing (NLP) for security analysis has been leveraged for identifying vulnerabilities in code, detecting phishing attacks, and automating security enforcement (Evans & Brown, 2021). The Zero Trust Security Model has gained prominence as organizations move towards stricter access controls and AI-driven authentication (Harris *et al.*, 2022). Lastly, Kernel-Level Monitoring has emerged as a critical security measure for detecting advanced threats that bypass conventional defenses (Wilson *et al.*, 2020). Despite these advancements, many AI-driven security solutions still rely on periodic updates, manual intervention, and predefined rules, making them vulnerable to sophisticated cyber threats. Our research builds upon these approaches by integrating reinforcement learning, federated learning, symbolic AI, and kernel-level monitoring into a self-evolving cybersecurity model capable of real-time threat detection, mitigation, and autonomous self-patching.

RESEARCH GAP

Despite significant advancements in AI-driven cybersecurity, existing solutions still face several critical limitations. Traditional security tools, such as IDS, IPS, and WAFs, rely heavily on predefined signatures and rule-based detection, making them ineffective against zero-day exploits and evolving attack patterns. While machine learning has improved anomaly detection, many AI-based systems struggle with high false positive rates, overwhelming security teams with irrelevant alerts. Moreover, adversarial attacks have shown that AI-driven models can be manipulated, leading to misclassification or complete evasion of security defences. This highlights the need for a more adaptive and resilient AI model that continuously learns from new threats while reducing false positives.

Another major gap lies in the lack of real-time, automated vulnerability patching. Current security frameworks, including EDR and SIEM, focus on detection and response but often require human intervention to deploy patches and mitigation strategies. Even with federated learning and global threat intelligence platforms, there is still a delay between threat identification and actual remediation. Furthermore, while reinforcement learning has been explored for cybersecurity, its application is limited due to the complexity of training AI agents in unpredictable attack scenarios. The integration of AI techniques such as symbolic reasoning and kernel-level monitoring is still in its early stages, leaving gaps in logical decision-making and low-level anomaly detection. The need for a unified, self-evolving cybersecurity model is evident. Current technologies operate in isolation, each addressing a specific aspect of cybersecurity but lacking seamless integration. Our research aims to bridge this gap by combining reinforcement learning for adaptive security responses, federated learning for collaborative intelligence, symbolic AI for logical reasoning, and kernel-level monitoring for deeper system analysis. This holistic approach ensures that cyber threats are not only detected in real-time but also mitigated and patched autonomously, eliminating the need for constant human intervention.

SUGGESTIONS

To overcome the challenges identified in the research gap, our AI-driven cybersecurity model introduces an integrated approach that combines multiple advanced techniques to enhance security, adaptability, and automation. By leveraging reinforcement learning, the model continuously refines its defence mechanisms based on real-time threat interactions, ensuring adaptive protection against evolving cyberattacks. Unlike traditional AI systems that require extensive retraining, our model dynamically adjusts its security strategies, reducing reliance on predefined signatures and improving detection accuracy. Additionally, the integration of federated learning allows security intelligence to be shared across different systems without exposing sensitive data. This decentralized approach enables faster detection of emerging threats and proactive mitigation, strengthening global cyber defence. Another key advancement in our research is the implementation of autonomous vulnerability patching, eliminating the delays caused by manual intervention in traditional security frameworks. Our model employs NLP-based vulnerability analysis to identify weaknesses in code, configurations, and system behaviour, generating immediate patches without disrupting operations. Furthermore, symbolic AI enhances logical decision-making, reducing false positives and improving the system's ability to differentiate real threats from benign anomalies. Kernel-level monitoring provides deep visibility into system processes, detecting stealthy malware and rootkits that bypass conventional security tools. By integrating these techniques into a single, self-evolving cybersecurity model, our research ensures real-time threat detection, mitigation, and self-patching, making cybersecurity not just reactive but predictive and autonomous.

CONCLUSIONS

Cybersecurity threats continue to evolve, becoming more sophisticated and capable of bypassing traditional security measures that rely on static signatures and human intervention. While AI-driven solutions have enhanced threat detection and response, they remain fragmented, reactive, and prone to high false positive rates. Many existing models still require manual oversight, slowing down the mitigation process and leaving critical systems vulnerable. Our research introduces a self-evolving AI cybersecurity model that overcomes these limitations by integrating reinforcement learning, federated learning, symbolic AI, NLP-based vulnerability detection, and kernel-level monitoring into a unified defence mechanism. This approach not only improves threat detection accuracy but also enables real-time autonomous mitigation and self-patching, eliminating the delays associated with manual security updates. By leveraging adaptive learning and real-time decision-making, our model ensures that security defences evolve alongside emerging threats, providing a proactive, predictive, and fully autonomous cybersecurity solution. This research marks a shift in cybersecurity from reactive response to intelligent, automated prevention, redefining how digital infrastructure is secured in an increasingly complex threat landscape.

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