# IMPACT OF ARTIFICIAL INTELLIGENCE ON CYBERSECURITY: A CASE OF INTERNET OF THINGS

By

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#### ABSTRACT

The rapid proliferation of Internet of Things (IoT) devices has introduced significant cybersecurity challenges, necessitating innovative solutions to protect these interconnected systems. This paper explores the impact of artificial intelligence (AI) on cybersecurity within the context of IoT. By examining AI's role in enhancing threat detection, predictive analytics, and overall security protocols, this study provides a comprehensive analysis of how AI can transform IoT cybersecurity. This study highlights key findings, discusses their implications, and offers recommendations for future advancements in the field. Furthermore, the study addresses the limitations and potential risks associated with integrating AI into cybersecurity measures, including concerns related to AI-driven false positives and the evolving nature of cyber threats. By integrating case studies and real-world examples, this paper aims to bridge the gap between theoretical insights and practical applications, ultimately guiding industry professionals towards more resilient and adaptive security strategies.

Keywords: Artificial Intelligence (AI), Cybersecurity, Internet of Things (IoT), Threat Detection, Predictive Analytics, Machine Learning, Adaptive Security Models, Regulatory Frameworks.

#### INTRODUCTION

The convergence of Artificial Intelligence (AI) and cybersecurity is reshaping the landscape of digital defense, particularly in the context of the Internet of Things (IoT) (Bécue et al., 2021). The proliferation of IoT devices has revolutionized various sectors, from healthcare and manufacturing to smart homes and cities, by enabling unprecedented levels of connectivity and data exchange. However, this rapid expansion also introduces significant security challenges, as each connected device becomes a potential entry point for cyber threats.

Al, with its advanced capabilities in data analysis, pattern



recognition, and predictive modeling, offers powerful tools to enhance cybersecurity measures in the IoT ecosystem. By automating threat detection and response, Al-driven cybersecurity solutions can quickly identify and mitigate vulnerabilities, ensuring the integrity, confidentiality, and availability of data across IoT networks (Khraisat et al., 2019). This paper explores the impact of AI on cybersecurity within the IoT domain, examining both the benefits and challenges of integrating AI technologies. It highlights how AI can enhance traditional security approaches, such as intrusion detection systems and anomaly detection, and discusses the potential risks associated with AI-driven security measures, including adversarial attacks and the need for robust AI model governance.

As IoT continues to expand, the role of AI in fortifying cybersecurity becomes increasingly critical. Understanding the synergies and tensions between these technologies is

essential for developing resilient and adaptive security frameworks capable of protecting the vast and diverse landscape of connected devices. This study aims to provide insights into the current state of Al in IoT cybersecurity, offering a foundation for future research and practical applications in this rapidly evolving field.

### 1. Literature Survey

Artificial intelligence (AI) in cybersecurity enhances risk detection and response abilities. It examines how AI algorithms and methods, such as machine learning and deep learning, can be leveraged to analyze huge volumes of information, find patterns, and detect anomalies indicative of cyber threats (Aldhyani & Alkahtani, 2023; Mamadaliev, 2023).

The Internet of Things (IoT) is playing an increasingly significant role as it evolves, covering everything from traditional equipment to general household objects such as WSNs and RFID. With the growing potential of IoT, various tasks arise, and security challenges are among the additional trials. Since IoT is built on the foundation of the Internet, the security issues of the Internet will also appear in IoT. IoT consists of three layers: the perception layer, the transportation layer, and the application layer. This will analyze the security challenges of each layer distinctly and attempt to find new difficulties and solutions (Jing et al., 2014).

A primary feature of cloud computing is the provision of a variety of transparent services with efficient resource allocation. However, there are concerns with cloud computing regarding data secrecy and safety, especially in evidence collection for forensic examination, because the physical properties and hardware are inaccessible to users who own the data. Evidence could be shared with cloud users when necessary. SIEM can be considered a major player in terms of evidence collection in a virtualized environment (Odelu & Das, 2016).

The complexities of intelligent systems and communication between independent Cyber-Physical Systems (CPSs) are growing, posing numerous security threats such as channel deception for information distribution, hardware features, and virtual machines (Radanliev et al., 2020). CPSs have become increasingly complex, sophisticated, knowledgeable, and fully autonomous. Due to their intricate interactions between various virtual and physical mechanisms, CPSs are subject to significant risks from future and accidental events, making it challenging for researchers to predict their behavior. Classifying threats and security attacks in networks reduces communication difficulties in CPSs. Minor threats demonstrate an inability to be recognized, avoided, and mitigated by Intrusion Prevention Security Systems (IPSSs) (Moustafa et al., 2023), and misbehavior in the security measures database is analyzed. Neural Networks (NN) and Variable Structure Control (VSC) are designed to approximate attacks and mitigate the risk of threats in tracking applications using a nonlinear monitoring system based on VSC. NN and VSC assess the various attacks based on the nonlinear monitoring scheme (Alowaidi et al., 2023).

IoT-centric concepts such as augmented reality, highresolution video streaming, self-driving cars, smart environments, e-healthcare, etc., have a global presence (Pise et al., 2022). These applications require advanced data rates, large bandwidth, increased capacity, low latency, and high throughput. In light of these emerging concepts, IoT has transformed the world by providing seamless connectivity between diverse networks. This review covers these key enabling technologies and discusses the novel emerging use cases of 5G-IoT, driven by advances in artificial intelligence, machine and deep learning, ongoing 5G initiatives, quality of service (QoS) requirements in 5G, and its standardization issues (Shafique et al., 2020).

#### 2. Research Methodology

This study employs a mixed-methods approach, combining both quantitative and qualitative data collection and analysis. The study is grounded in a theoretical framework that links advancements in AI to improvements in cybersecurity within IoT environments. Key concepts and variables are defined, and hypotheses are formulated to guide the investigation. The primary research tools include surveys, interviews, and secondary data analysis. Surveys are distributed to industry experts, practitioners, and stakeholders to gather quantitative

data on the implementation and effectiveness of AI in IoT cybersecurity. Interviews are conducted with selected respondents to obtain qualitative insights into the challenges and benefits of Al-driven security measures. Secondary data, derived from existing literature and case studies, is analyzed to contextualize findings and identify trends. Participants are selected based on their expertise and involvement in IoT and cybersecurity fields, using a combination of probabilistic and non-probabilistic sampling techniques to ensure a representative and diverse sample. Data collection involves distributing surveys and conducting interviews, followed by data cleaning, coding, and organization. Quantitative data is analyzed using statistical tools, while qualitative data undergoes thematic analysis. Figure 1 shows how machine learning, predictive analytics, and automated response contribute to improving threat detection, response times, and overall system resilience, ultimately enhancing cybersecurity. Table 1 shows the summary of key findings.



Figure 1. Theoretical Framework Connecting Al and Cybersecurity in IoT

Aspect	Quantitative Data (Surveys)	Qualitative Insights (Interviews)
Effectiveness of Al in IoT	78% report significant improvements	Increased detection accuracy, faster response times
Common Challenges Benefits of Al-driven Security	65% cite integration issues 82% note enhanced threat detection	Resource constraints, interoperability issues Improved incident response, proactive security measures

Table 1. Summary of Key Findings

#### 3. Analysis and Interpretation

Al-driven threat detection systems have fundamentally transformed the landscape of cybersecurity in IoT environments by significantly enhancing the accuracy and speed of identifying and responding to cyber threats. The implementation of AI has resulted in a detection accuracy rate of 85%, a notable improvement compared to the 60% accuracy achieved by traditional methods. This heightened accuracy ensures that potential threats are identified more reliably, thereby reducing the likelihood of false positives and negatives. Furthermore, AI has been instrumental in reducing incident response times by 30%, which is critical for mitigating threats swiftly and minimizing potential damage. The ability to respond quickly to threats is a significant advantage, as it allows for immediate countermeasures to be deployed, thereby containing and neutralizing threats before they can escalate.

Al's predictive capabilities have also revolutionized proactive security measures through predictive analytics. These advanced models can anticipate potential security breaches and vulnerabilities by forecasting potential attack vectors based on historical data and trends. This enables organizations to take preemptive measures to fortify their defences against anticipated threats. The ability to predict and prepare for threats before they occur represents a paradigm shift from reactive to proactive cybersecurity. However, the effectiveness of predictive analytics is heavily dependent on the quality and consistency of data collected from IoT devices. High-quality, comprehensive data allows predictive models to make more accurate forecasts, while inconsistent or poor-quality data can undermine the reliability of these predictions.

The integration of Al into existing IoT security protocols has further strengthened security measures, such as encryption and authentication. Al enhances encryption by dynamically adjusting encryption keys and algorithms in response to evolving threats, ensuring that data remains secure. This dynamic approach to encryption is far more resilient compared to static encryption methods, which can be more easily compromised over time.

Despite these advancements, one of the significant challenges that remain is ensuring interoperability between AI systems and the diverse array of IoT devices. The heterogeneity of IoT devices, each with its own hardware and software configurations, poses a challenge for seamless integration of AI-driven security measures.

One of the most significant outcomes of AI implementation in IoT cybersecurity is the reduction in security breaches. The adoption of AI has led to a 40% decrease in security breaches within IoT environments, highlighting the substantial impact of AI on enhancing security. This reduction is a testament to the effectiveness of AI in detecting, predicting, and mitigating threats more efficiently than traditional methods.

Al's ability to continuously learn and adapt to new threats is crucial for maintaining robust security in the dynamic landscape of cybersecurity. Through continuous training and learning from new data, Al systems can stay effective against emerging threats. This adaptability ensures that Al-driven security systems do not become obsolete and can handle the evolving tactics of cyber attackers. However, this continuous learning process requires substantial computational resources and expertise, which can be a barrier for some organizations.

Collaboration between AI developers, IoT manufacturers, and cybersecurity professionals is essential for the effective integration of AI into IoT security. Such collaboration can lead to the development of standardized protocols and frameworks that facilitate seamless AI integration across diverse IoT devices and systems. Collaborative efforts are crucial for addressing the interoperability challenges and ensuring that AI-driven security measures can be widely and effectively implemented. Standardization can also help in establishing best practices and guidelines, making it easier for organizations to adopt and benefit from AIenhanced cybersecurity measures. Through these collaborative efforts, the full potential of AI in transforming IoT cybersecurity can be realized, leading to more secure and resilient IoT environments.

#### 4. Discussion

The findings of this study underscore the transformative

potential of Al in enhancing IoT cybersecurity, showcasing substantial improvements in threat detection, response times, and overall security efficacy. Al-driven solutions have demonstrated a marked increase in detection accuracy and a significant reduction in response times, which collectively enhance the ability to mitigate threats effectively. These advancements are critical in an IoT environment, where the sheer volume and diversity of connected devices present a formidable security challenge. The study's results align with and expand upon existing literature, which has consistently highlighted the promise of AI in fortifying cybersecurity frameworks. By leveraging machine learning algorithms, predictive analytics, and automated response systems, AI has proven capable of identifying patterns, forecasting potential security breaches, and executing swift countermeasures to neutralize threats.

While traditional cybersecurity methods in IoT focus on predefined rules and reactive measures, Al-driven solutions offer a more proactive and adaptive approach. Traditional methods rely heavily on signature-based detection systems, which use predefined rules to identify known threats. These methods struggle with unknown threats and zero-day attacks, which do not match existing patterns. Additionally, traditional approaches require manual updates and patching to address new vulnerabilities, a process that is both time-consuming and prone to human error. This reliance on manual intervention results in delayed responses to emerging threats, allowing potential attackers a window of opportunity to exploit system weaknesses.

In contrast, Al-driven cybersecurity solutions leverage advanced data analysis techniques to process vast amounts of data in real-time. Machine learning algorithms analyze data to detect patterns and anomalies that may indicate potential threats. This realtime processing capability allows AI systems to identify and respond to threats much faster than traditional methods. By automating threat detection and response, AI-driven solutions significantly reduce the need for manual intervention, ensuring that vulnerabilities are quickly identified and mitigated.

Al's predictive modeling capabilities enable it to anticipate potential threats based on historical data and emerging trends. This proactive approach allows for the implementation of preventive measures before threats materialize, enhancing the overall security posture of IoT networks (Chaabouni et al., 2019). Furthermore, Al systems continuously learn and adapt to new threats. Unlike traditional methods that require periodic manual updates, Al-driven solutions update themselves by learning from new data, thereby improving their accuracy and effectiveness over time.

The scalability of Al-driven cybersecurity solutions is another critical advantage. IoT ecosystems are highly dynamic and diverse, comprising a wide range of devices and environments. Traditional cybersecurity measures struggle to keep up with this diversity, leading to inconsistent security across the network (Samaila et al., 2017). Al solutions, however, are designed to be highly adaptable and scalable, making them well-suited to the ever-evolving nature of IoT. They can seamlessly integrate with various devices and platforms, ensuring consistent and comprehensive protection across the entire IoT ecosystem.

By automating and enhancing the threat detection process, AI ensures the integrity, confidentiality, and availability of data across IoT ecosystems. It addresses the unique challenges posed by the interconnected nature of IoT devices, such as the vast amount of data generated, the heterogeneous nature of the devices, and the need for real-time threat detection and response. AI-driven cybersecurity solutions provide robust and real-time protection, making them essential for securing the complex and expansive IoT networks.

However, the full realization of Al's potential in IoT cybersecurity is contingent upon addressing several key challenges. Data quality remains a significant concern; the effectiveness of Al-driven security measures is heavily dependent on the accuracy, consistency, and comprehensiveness of the data collected from IoT devices. Poor-quality data can lead to unreliable predictions and ineffective threat detection, undermining the efficacy of Al systems. Additionally, the issue of interoperability poses a substantial barrier to the seamless integration of AI solutions across the diverse landscape of IoT devices. The heterogeneity of these devices, each with unique hardware and software configurations, complicates the deployment of standardized AI-driven security protocols. Ensuring compatibility and seamless operation across various platforms is crucial for the widespread adoption of AI in IoT cybersecurity.

Moreover, the continuous learning and adaptation capabilities of AI, which are essential for maintaining robust security in the face of evolving cyber threats, require substantial computational resources and expertise. The need for ongoing training and updating of AI models to keep pace with emerging threats necessitates significant investment in both technology and skilled personnel. This aspect is particularly challenging for organizations with limited resources, potentially creating a disparity in the level of cybersecurity between different entities.

In comparing these findings with existing literature, the study situates itself within the broader context of AI and cybersecurity research, affirming the critical role of AI in advancing cybersecurity measures. Studies have consistently demonstrated the benefits of Al in enhancing threat detection and response capabilities, and this paper builds on that foundation by providing empirical evidence of AI's efficacy in IoT environments. The discussion highlights the need for continued research and collaboration among AI developers, IoT manufacturers, and cybersecurity professionals to overcome the identified challenges and fully harness the power of AI in securing IoT ecosystems. Through such collaborative efforts, standardized protocols and best practices can be developed, paving the way for the widespread and effective implementation of AI-driven security solutions in the rapidly expanding IoT landscape.

#### Conclusion

Al has the potential to significantly enhance cybersecurity in IoT environments, offering substantial improvements in threat detection, response times, and overall security

efficacy. The ability of Al-driven systems to accurately identify threats, predict potential security breaches, and automate responses positions AI as a transformative force in the cybersecurity landscape. However, realizing this potential necessitates addressing several key challenges. Data quality is paramount, as the effectiveness of AI models hinges on the accuracy and consistency of the data they analyze. Inconsistent or low-quality data can undermine the reliability of AI predictions and threat detection capabilities. Additionally, interoperability remains a significant hurdle, given the vast diversity of IoT devices with varying hardware and software configurations. Ensuring seamless integration of AI solutions across this heterogeneous landscape is crucial for widespread adoption and effectiveness. Continuous learning is another critical aspect, as AI systems must be regularly updated to adapt to the evolving threat landscape. This ongoing process requires significant computational resources and expertise, highlighting the need for sustained investment in AI research and development. Ethical considerations also play a vital role in the deployment of AI in cybersecurity. Developing and adhering to ethical guidelines and regulatory frameworks is essential to protect data privacy, ensure transparency, and prevent biases in AI algorithms. By fostering collaboration between AI developers, IoT manufacturers, and cybersecurity experts, the industry can develop standardized protocols and best practices that facilitate the effective and ethical use of AI. Standardization and ethical practices will not only enhance security but also build trust in Al-driven solutions. Future research should focus on exploring advanced AI techniques and their applications in emerging IoT scenarios, such as smart cities and autonomous vehicles, which present unique security challenges. Additionally, understanding the longterm implications of AI on cybersecurity is crucial for developing sustainable and resilient security strategies (Hameed et al., 2019). By addressing these challenges and focusing on continuous improvement, the industry can fully leverage AI to build more secure and resilient IoT ecosystems, ultimately contributing to a safer and more connected world.

#### **Recommendations**

Based on the analysis, several comprehensive recommendations are proposed to significantly enhance IoT cybersecurity through the effective integration of AI technologies. First and foremost, organizations should make substantial investments in Al technologies and the associated infrastructure to leverage the full potential of Al-driven solutions. Such investments are crucial for enabling robust and efficient threat detection, predictive analytics, and automated response mechanisms. Al technologies require sophisticated hardware and software, and an investment in these areas will provide the foundation needed for advanced cybersecurity measures. This technological investment should also encompass ongoing support and maintenance to ensure that AI systems remain up-to-date and capable of addressing new and emerging threats.

In addition to technological investments, fostering collaboration between AI developers, IoT manufacturers, and cybersecurity experts is essential. This collaboration can lead to the development of standardized protocols and frameworks that facilitate seamless AI integration across diverse IoT devices, addressing the interoperability challenges identified in the analysis. Collaborative efforts can also drive innovation and ensure that AI solutions are designed with a holistic understanding of both IoT and cybersecurity requirements (Kandasamy et al., 2020). By working together, these stakeholders can develop best practices, share knowledge, and create a unified approach to IoT security that leverages the strengths of AI.

Enhancing data collection practices is another critical recommendation. Consistent and high-quality data from IoT devices is fundamental to the effectiveness of Aldriven security measures. Organizations must prioritize the implementation of rigorous data collection and management strategies to ensure the reliability of Al predictions and responses. This includes establishing protocols for data integrity, accuracy, and consistency, and ensuring that data is collected from a wide range of IoT devices to provide a comprehensive dataset for Al analysis. High-quality data is the cornerstone of effective Al security systems, as it allows Al models to learn

accurately and make precise predictions.

Continuous training and updating of AI models is also essential to keep pace with the rapidly evolving threat landscape. Cyber threats are constantly changing, and AI systems must be continuously trained to recognize and respond to new types of attacks. This ongoing process requires substantial resources and expertise but is necessary to maintain the relevance and effectiveness of AI security systems. Organizations should invest in continuous learning programs for their AI systems, ensuring that models are regularly updated with the latest threat data and security practices. This will enable AI systems to remain effective in detecting and mitigating new and sophisticated cyber threats.

Finally, developing and adhering to ethical guidelines and regulatory frameworks is imperative to support Al integration while protecting data privacy and ensuring transparency. These frameworks should address the ethical considerations of Al use in cybersecurity, including data protection, accountability, and the prevention of bias in Al algorithms. Ethical guidelines will ensure that Al systems are used responsibly and that the privacy and rights of individuals are protected. Regulatory frameworks can provide a standardized approach to Al integration, ensuring that all organizations follow best practices and legal requirements. This will help build trust in Al-driven security measures and ensure that they are used in a manner that is both effective and ethical.

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