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Research Article

AI-Driven Cybersecurity: Leveraging Machine Learning For Enhanced Iot Threat Detection And Mitigation

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ABSTRACT

Given the vast proliferation of Internet of Things (IoT) devices in our world, these have become an increasingly attractive target to cyber adversaries. It is thus particularly important to continuously be able to assess their overall security posture, detect various anomalous activities, and respond to real-time adversarial attacks leveraging these devices for malicious purposes.
This article presents work in progress on the development of a novel Integrated AI-driven IoT Intrusion Detection Mechanism, called IA2IDM. It works by deploying a Random Forest classifier trained on sets of features generated from an array of datasets from IoT device traffic.Although our preliminary results indicate that achieving a 99% detection rate may not be feasible due to the challenge of having access to adequate training data in the area of IoT networks for defense purposes, we conclude this article by discussing the lessons learned, the promise, and the potential of IA2IDM. It also provides a roadmap on how IA2IDM systems can be developed with sufficient and demonstrable AI confidence and deployed in real-life settings to protect IoT devices now and into the future.

Keywords:AI- Driven Cybersecurity, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM),Computer Science, Data Science,Vehicle, Vehicle Reliability

1. Introduction

As the promise of the Internet of Things (IoT) continues to materialize, both public and private organizations across the globe are increasing investment in IoT devices. The growing deployment of a myriad of IoT devices, ranging from simple sensors and smart cameras to complex industrial control systems, is expected to support smart cities, improve healthcare, enable a range of innovative services, and increase supply chain efficiencies. As the IoT continues to expand, it takes center stage in cybersecurity. Attacks on IoT systems have garnered significant attention, prompting studies evaluating how they may be subject to traditional cyber attacks that were once confined to computers and networks.

Furthermore, many IoT devices are susceptible to relatively simple attacks because basic security protocols are often not implemented.Artificial Intelligence (AI) encompasses several machine learning algorithms. The promise of AI in resulting in high accuracy for specialized tasks is married with the current economical availability of powerful hardware which significantly diminished the computational cost of training and running models. As a result, the use of advanced AI and machine learning techniques in cybersecurity has experienced a boost in research as well as commercial applications.

In the vast array of applications of AI-driven cybersecurity techniques, the detection of self-propagating malware could be considered a classic. Malware continuously evolves and adapts to dodge traditional detection solutions at an ever-increasing rate, and novel attacks using automated malicious software are now able to target new vulnerable devices at a similarly increasing rate. IoT malware leverages a swarm approach, using large numbers of infected (or honest) devices for (1) command and control capabilities, (2) computing resources e.g., mining cryptocurrency, or (3) as vectors for further infection. It is therefore a pressing need to detect malware targeting IoT devices in the first instance.

Fig 1: Important IoT Application Domains.

1.1. Background and Significance

In recent years, devices within the Internet of Things (IoT) have become a popular target for attackers. Unlike traditional targets such as servers, IoT devices often run diverse software and have significant hardware limitations, making them more vulnerable. In some cases, IoT botnets can be very large and powerful due to the sheer number of vulnerable devices. Current defenses aggregate IoT traffic and apply a diverse collection of machine learning classifiers. These interconnected components may be used together to identify certain types of attacks. However, they can be expensive in terms of computational resources when applied at scale, may miss novel threats, or even be evaded by an attacker who is aware of the defense.In this work, we propose a multi-profiling strategy to make it both easier to diversify the inputs to classifiers and more effective at identifying the latest, most significant IoT threats. We apply profiled models alongside generic ones and show that while it is important to profile our models, we can do so much more easily than creating and tuning the entire model. We find that by profiling models we can largely identify the same set of top indicators and achieve similarly high detection rates while making it much harder for attackers to evade all detection altogether. Our results suggest that our approach would provide substantial additional defense capability when run at scale.

1.2. Research Aim and Objectives

The intended research distinguishes itself from previous studies, as it primarily focuses on the application of a novel AI model to tackle IoT-related security challenges. The primary aim of the study is to create and utilize a complex AI model, built on an ensemble of machine learning algorithms, to perform IoT device behavioral analysis for its application in the early detection and accurate classification of IoT-derived vulnerabilities. It specifies the end-user device type, as well as security vulnerabilities, such as Man-in-the-Middle (MITM) attacks, in which an attacker intercepts traffic between the end devices and the server, which could allow them to read or even manipulate the data being sent or received.

The following objectives will be pursued to meet the research aim:- Systematically explore the best-performing individual machine learning algorithms to be included in the ensemble model, created for the real-time detection and classification of the observed IoT device behaviors, and earnestly expand the foundation for this AI-driven security approach. - Systematically combine machine learning algorithms into an optimized AI ensemble model and address misconceptions of their aggregated decision-making strategies, designed to enhance the robustness of the final solution. - Address limitations of previous AI-driven IoT device security solutions and further expand the understanding of IoT device behaviors through the utilization of ensemble strategies.

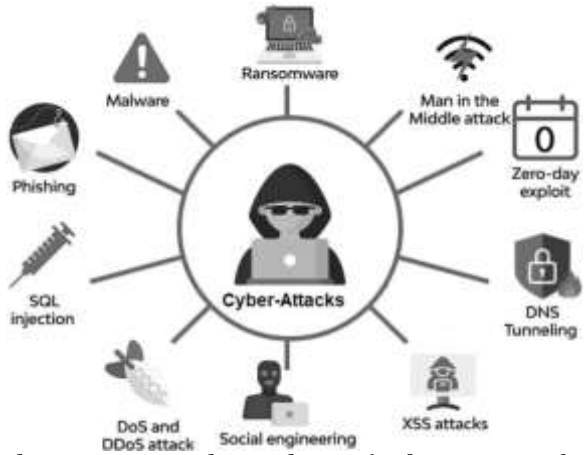

Fig 2: Several Common Attacks or Threats in the Context of Cybersecurity

2. Fundamentals of AI in Cybersecurity

AI techniques can augment cybersecurity approaches by enabling advanced predictive capabilities against future attacks and defense (i.e., "predict, detect, autonomous defend, and respond"). There are various machine learning paradigms such as supervised, unsupervised, reinforcement, and zero-shot learning, among others, that could be used to predict attacks and detect security threats based on modeled data and historical data patterns locally or in the cloud or hybrid cloud environments. In unsupervised machine learning approaches, labeled datasets are usually not required.In reinforcement learning (RL), agents learn action-outcome maps called policies via repeated reward-guided learning. Reinforcement learning in cybersecurity could be challenging as the input state space could be practically infinite, and the experimentations with the real world may be costly or impractical. Zero-shot learning primarily allows the extensibility of existing machine learning models to identify newer classes of threats that were not included in the training dataset. Deep adversarial learning has shown remarkable results in detecting foreground anomalies in real-world data. Another key challenge in AI for cybersecurity is to have adjustable machine learning models that can dynamically modify their configurations and detect advanced threats in real time.AI techniques have revolutionized cybersecurity by offering capabilities beyond traditional methods. Supervised learning allows for the classification of known threats based on labeled data, while unsupervised learning can detect anomalies and previously unknown attacks by analyzing patterns in unlabeled data. Reinforcement learning, though challenging due to the vast state space and costly real-world experimentation, offers promise in developing autonomous defense systems that can adapt to evolving threats based on feedback mechanisms.Zero-shot learning expands the horizon by enabling models to generalize to new, unseen types of attacks, thus enhancing the resilience of cybersecurity defenses. Deep adversarial learning, a subset of generative adversarial networks (GANs), has demonstrated effectiveness in detecting subtle anomalies amidst complex datasets, making it a potent tool for anomaly detection in real-world cybersecurity scenarios. However, ensuring the agility of AI models to dynamically adjust configurations and responses in real-time remains a critical challenge to stay ahead of sophisticated adversaries in cyberspace. Integrating these diverse AI paradigms promises to fortify cybersecurity frameworks with advanced predictive, defensive, and responsive capabilities against evolving threats.

Fig 3: AI in CyberSecurity

1.1. Machine Learning Basics

The following subsections provide a high-level overview of the basic concepts and terminology used in machine learning that help lay the groundwork for further topics in this comprehensive research work. Perhaps one of the most basic concepts of machine learning is the idea of "generalization" since the ultimate goal is to support the construction of predictive models that perform good predictions on previously unseen, new data. The availability of a fundamental set of concepts that helps guide the construction of reliable predictive models

is paramount and it should also help foster the effort of promoting the responsible development and use of artificial intelligence. The first step in the implementation of such models is that of defining a set of dependable characteristics or properties. Since this initial list may be very long and difficult to determine, sometimes it may be a more feasible approach to define not what the characteristics of the predictive model are in terms of properties, but instead what such properties of the model are not. The notion of Occam's razor is paramount for such a strategy and states that one should not make more assumptions than needed and prefer the simplest solution in case of many viable models able to predict a certain behavior.
Table 2 shows a list of the main concepts in machine learning and their associated explanations. The following sections provide a more in-depth explanation of the goals and ideas behind such concepts and their role in the development of solid predictive models that can aid the development of AI-powered cybersecurity solutions with the ultimate goal of enhancing the detection and mitigation of threats posed to the Internet of technology landscape of resource-constrained and pervasive computing devices.

2.2. AI Applications in Cybersecurity

Artificial intelligence (AI) is a supplier of cognitive technologies that are capable of learning their environment, reasoning to reach resolutions, and turning what they have learned into executed actions. Currently, AI is being used to support physical security, digital cybersecurity, and operating system (OS) security. In digital cybersecurity, machine learning (ML) is often used to investigate and contrast large datasets to close in on a decision for a given sample. In physical and OS security, AI focuses on protection and defense in real-time. By using AI for system security, you can find, prevent, and stop OS threats. Because the format of each of these machine-talking items of data is separated, this technology then presents these as easy-to-view data for people to understand, allowing people to understand the state of each of the hefty objects. AI can be programmed to find and draw attention to only those activities that are abnormal and which pose security risks. The model of the AI system used for physical, OS, and DL security also offers an intuitive view of the entirety of data, improving not only the quality of surveillance but also its reaction times against abnormalities.

3. IoT Security Challenges

A large number of security threats in IoT devices stem from their resource-constrained nature, lack of update mechanisms, and their broad distribution, which ultimately leads to serious security challenges. IoT devices are often viewed as easy targets and they tend to suffer from a nonexistence of effective security mechanisms, lack of timely security updates, embedded quality, and a complete self-managed life-cycle resulting in very high costs for managing and supporting embedded software updates in a large number of deployed IoT devices.Traditional desktop, server, and network security relies on features such as antivirus software, firewalls, and IPS/IDS systems which specialize in detecting known threats. The security industry traditionally recognizes unknown threats by heuristic detection algorithms, behavioral detection, and whitelisting methodologies. These solutions have negative impacts on the system performance while causing compatibility problems with certain software. Over the years, traditional security solutions have been losing ground to machine learning (ML) and deep learning (DL) to protect this growing number of devices, identifying unknown threats through the use of scarce resources, to protect these growing numbers of vulnerable devices. With the advent of technological breakthroughs, a variety of decision-making models have been developed, these include supervised, unsupervised, and reinforcement learning models in DTs, over generic ANN structures and clustering methods, up to powerful customized DNN architectures, and more recently combining AI models for combined decision factors.

3.1. Unique Threats Posed by IoT Devices

Advances in IoT are transforming mass communications and enabling wide-area intelligent sensing with numerous applications spanning business, medical, and consumer domains. These developments have driven explosive growth in the number, diversity, and connectedness of IoT devices. However, IoT security is lagging behind the growth of the technology, leaving many IoT devices vulnerable to exploitation by sophisticated attackers. The small sizes and processing capabilities, along with the often severe power constraints and small storage capabilities, of many IoT devices make traditional security approaches impractical or ineffective.Researchers and security experts have been calling attention to the unique threats posed by IoT devices for almost a decade. Unlike desktops, servers, laptops, avionics, or other more traditional computing devices, IoT devices have the potential to be deployed on a massive scale across a wide variety of applications and environments, using a highly diverse set of platforms, and with even more varied processing, communication, and sensing capabilities. This volume and extreme diversity give novel convergence attack capabilities to potential adversaries. For example, IoT vulnerabilities can enable adversaries to surreptitiously subvert an implanted medical device, repeatedly capture proprietary or sensitive business data from compromised office machines and personal appliances such as phones, wives, refrigerators, or thermostats, surveil personal or public spaces using video or audio captured by web-enabled surveillance, doorbells, or appliances, disrupt the service operations of high-scale systems, or illuminate a dark house's interior from a distance.The rapid proliferation of IoT devices across various sectors has introduced unprecedented connectivity and intelligence into everyday operations. This transformation spans industries such as

healthcare, where IoT facilitates remote patient monitoring and personalized medicine, and in smart cities, where sensors optimize traffic flow and energy consumption. However, the security landscape for IoT remains precarious due to inherent vulnerabilities stemming from constrained resources like processing power and memory. Traditional security measures designed for conventional computing devices often struggle to adapt to the scale and heterogeneity of IoT ecosystems.Security experts have long warned about the unique risks posed by IoT devices, which unlike traditional computers, are deployed ubiquitously and in diverse environments. This diversity not only complicates security protocols but also amplifies the potential impact of security breaches. For instance, compromised IoT devices can compromise privacy by surreptitiously recording audio or video, or disrupt critical infrastructure systems essential for public safety and service continuity. The convergence of these vulnerabilities provides malicious actors with new avenues for attacks that could undermine both personal privacy and organizational security on a vast scale.Addressing these challenges requires innovative approaches that consider the specific constraints and use cases of IoT devices. Strategies such as secure-by-design principles, where security is integrated into the device from its inception, and the development of lightweight cryptographic protocols are essential steps towards mitigating IoT security risks. Furthermore, ongoing collaboration between industry stakeholders, policymakers, and researchers is crucial to establish robust standards and regulations that promote IoT security without stifling innovation. By prioritizing cybersecurity in tandem with technological advancement, we can harness the full potential of IoT while safeguarding against its inherent vulnerabilities.

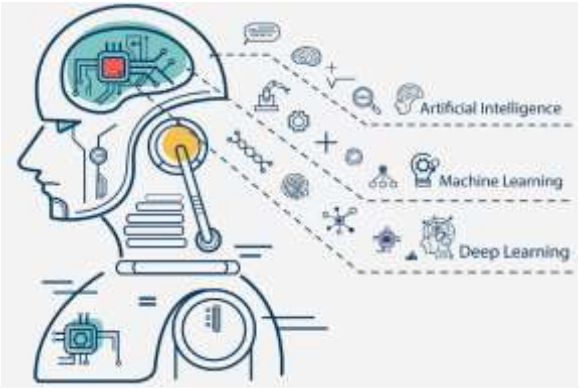

Fig 4: AI in Cyber Security - Use Cases, Risks and Challenges

3.2. Vulnerabilities in IoT Networks

In the context of IoT, vulnerabilities may appear in three layers: physical layer (e.g., RFID); network layer (e.g., Zigbee, BLE); and application layer (e.g., HTTP, CoAP). Every layer is subject to different types of vulnerabilities.

At the physical layer, transponders can easily be cloned, as they are unable to differentiate between the tags and the readers. Similarly, readers can be spoofed since they use standard RFID transponders as unique identifiers. Using two transponders with the same identifier, an attacker can clone the device to gain access to an IoT system, using either brute force attacks or software-defined radio.

On the network layer, Zigbee showed major security flaws because devices connect directly to the coordinator since the network is a single hierarchical star. BLE hosts an advertising mode that constantly broadcasts the presence of the devices but does not notify trespassers. Both Zigbee and BLE are vulnerable to unauthorized access, content tampering, and traffic sniffing.

At the application layer, most vulnerabilities are related to the protocols utilized to connect a device or with remote communication and data collection. For instance, HTTP is not reliable for remote sensor data collection. CoAP, an IPv6, and ULC-based Web services protocol, is more appropriate but also has known

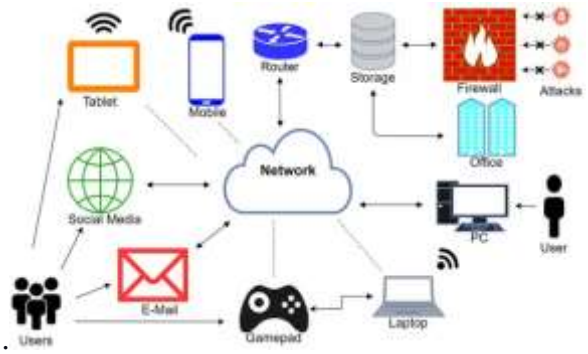

Fig 5: General Representation of an IoT System.

2. AI-Driven IoT Threat Detection

AI-driven IoT threat detection addresses a critical and unsolved aspect of IoT security. The use of supervised learning in conjunction with IoT credential datasets offers an enriched dataset for threat identification. This model can be trained to utilize credential leaks and the inventory of "hacked devices" to better understand what has been breached. This ground truth is rare in cybersecurity and provides significant enterprise value. The use of machine learning models applied to IoT infrastructures allows organizations to deter cybersecurity threats, in addition to creating awareness of the type of IoT devices that are more susceptible to an attack. This machine learning model is trained and fed with a mixture of IoT credential leaks datasets, multi-asset IoT management platforms, and the inventory of "hacked devices" provided by threat intelligence and cybersecurity research organizations. These datasets are pre-processed, anonymized, and labeled with ip2geolocation, and feature engineering is applied for IoT device information extraction. This AI-driven approach allows the characterization and identification of IoT device types, CVEs, and potential vulnerabilities.

4.1. Role of Machine Learning in IoT Security

Machine learning enables machines to learn from experience, i.e., large amounts of data, and improve their performance over time. This is potentially very useful for a wide range of security-related problems. In the fields of IT security (information technology) and industrial automation, for instance, many new diagnostics, decision-support, or mitigation tools could be developed by organizations to proactively detect existing as well as novel attacks and vulnerabilities. In this paper, we argue that security expertise in strategic positioning and coupling of cyber-physical assets with security layers and data islands, and machine learning could be beneficial throughout the entire value chain, especially considering that most of the interesting security applications are in the form of closed-loop systems. We consider the lifecycle of an Internet of Things (IoT) device positioned in an Industry 4.0 environment, exploring artificial intelligence (AI) as one of several relevant security technologies and discussing the major limitations and requirements as well as suggestions for further research.Concerning current best machine learning practices to mitigate IoT threats, we conclude that research on the identification of detector boundaries and the learning of extremely low energy inference to induce interference or backdoor attacks is still in its infancy. Moreover, we argue that, due to future optimization related to the minimization of data movement and sensory-based data processing, frequently combined with process knowledge not encompassed in training data leading to further reduced information for learning mechanisms, mass-scale data-exchange networks could become a sub-optimally expensive security technology. We do not discuss further general digitization challenges, including privacy, legal, and political implications, as accompanying weaknesses that could ultimately continue to undermine the full potential of an optimized machine learning-driven Internet of Production.

4.2. AI Models for Threat Detection

The initial step is to extract the features, which are unique to a particular frame that distinguishes it from other frames - both benign and malicious. Based on the physical and Link Layer peculiarities, four features can be extracted: amplitude, energy, random value, and cross auto-correlation of the received signal. Once the features are extracted, models are trained for supervised learning. This training, like any other machine learning model, requires a high-quality labeled dataset. MIT IoT Dataset for Cyber Security from AWS is utilized, which contains communications of approximately 80 smart devices that are involved in over 20 distinct malicious activities. Once trained, the classification model accurately identifies most of the existing threats. Finally, the deployment and implementation models are optimized for real-time wire speed handling and interface visualization.The packets are clustered in such a manner that the characteristics and pattern of grouping deterministically discern the behavior of similar devices from dissimilar objects. Using comprehensive metrics and statistics from the dataset, unsupervised clustering methods isolate acoustic communication patterns that depend on factors like interaction, mobility, spatial structure, and action. The target of interest, type, or content is not of primary importance. Therefore, tornadic clustering of visible and definitive logical groups (clusters) of hidden objects fabricate groups with internal similarity and external variance. Finally, these methods are enhanced to cluster newly detected devices and networks to amplify the current security suite with NEMO

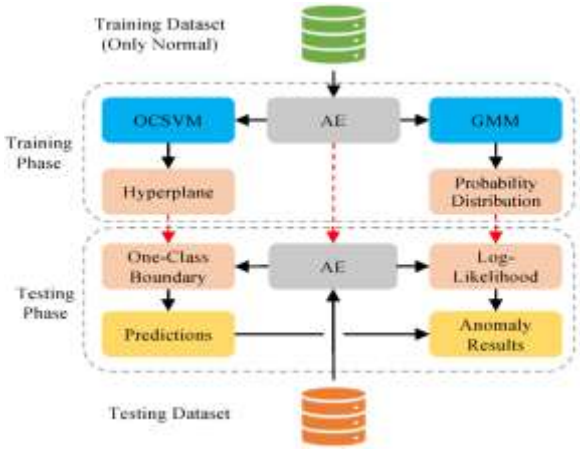

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Fig 6: The Proposed Detection Framework.

5. Case Studies and Applications

In recent years, the use of machine learning has resulted in innovative, next-generation IoT solutions. In this section, we provide four different case studies and applications that leverage machine learning to provide enhanced security and advance the performance of IoT devices and applications. It is noteworthy that all these solutions are already capable of being employed in practice and provide not only theoretical but very practical contributions to the science of AI-enabled IoT security applications and should be used by those interested in applying real-world and practical IoT solutions.Autonomous Cyber-Physical Systems for the Aging Society. The "Swarm of Drones" is part of the project "Autonomous Cyber-Physical Systems for the Aging Society" funded by the Spanish National Research Program. The Reflection-Aware Cyber-Physical System (CPS) uses a multi-source sensor system that enables a novel kind of surveillance and inspection of specific scenarios to improve and protect the individual privacy and information security of the people inside them. The reflection-awareness uses a diversity of sensors to merge the information from very different sources, e.g., taking advantage of both optical visible cameras and thermal cameras for object detection purposes. The Reflection-Aware Cyber-Physical System (CPS) has a wide application range, going from surveillance to automatic people counting, automatic lost objects retrieval, drone patrolling, assisted living, etc.

5.1. Real-World Implementations of AI in IoT Security

Today, most companies and smart city applications have adopted and deployed the IoT in sectors such as agriculture, health, transportation, and entertainment. However, these systems are insecure and vulnerable to attacks that can have serious ramifications. AI is the science of enabling machines to perform complex tasks that typically require human intelligence. AI has been useful in IoT security. It helps by protecting an individual's privacy and IoMT from cyber attacks. The three most common AI processes used for such security measures are Supervised Learning, Unsupervised Learning, and Reinforcement Learning. In addition to robotic security, AI plays a crucial role in AI-driven IDS, real-time prediction of medical IoT using CNN, efficient authentication, and secret key extraction with the incorporation of AI models. The deep learning model has proven to increase security at various levels when it comes to AI Security applications. The list is endless and the dynamics are forever changing. AI also eases the facilitation of mobile data image caching while safeguarding privacy, boosting neural network performance, and ensuring network defense and security. In conclusion, AI in IoT security not only offers a lightweight design that enhances the security features but also provides a more stable security model that is among other things also less prone to tampering and interruption. AI implementation in IoT is an attack, not a defensive mechanism. The mechanism indeed is the safeguard against attacks.

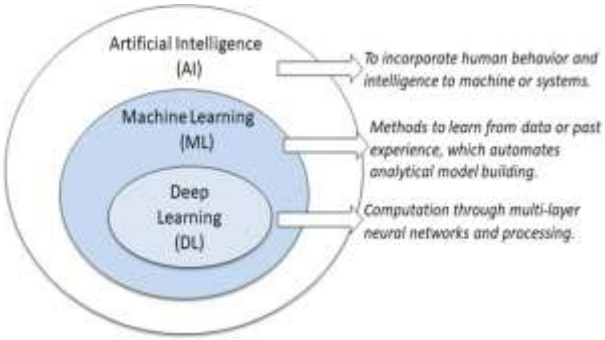

Fig 7: An Illustration of Machine Learning (ML) Including Deep Learning (DL) Relative to Artificial Intelligence (AI)

6. Challenges and Future Directions

One of the main challenges when dealing with new IT environments is the policy configuration (values and naming) since these can change when the application is installed. Given that we concentrate on IoT devices, in a real-world scenario, we cannot predict which devices are connecting, and their usage/installation by a regular (non-technical) user. Recent cybersecurity surveys show that the majority of the analyzed IoT devices do not allow for secure configuration. Also, as AI is vulnerable to adversarial examples, which are inputs crafted to confuse the AI model and are fed to the AI system to cause misclassification of its output, specific issues arise when we discuss these adversarial attacks. Not only do we need to prevent these attacks in the device network, but we also need to guarantee that these do not cause malfunctioning of the security model developed. Another important aspect is the fact that there is a tradeoff between a high-performing and robust model and the energy and time that it requires to execute.The field of AI-driven cybersecurity should be explored further, particularly in the IoT context. Novel algorithms and methodologies should be researched to help improve model performances, reduce model time complexity, and increase the robustness of deep learning models. To be able to develop multiple solutions to improve security detection at different detection levels, granular models should be designed. The performance and feasibility of these models should then be tested. Finally, AI-security mechanisms should cater to the context of both attackers and defenders of the AI's output since concepts such as these appear to continuously evolve and their impacts on society and the market should be taken into account.

6.1. Ethical Considerations in AI-Driven Cybersecurity

With the rapid emergence of solutions that use AI and big data in the area of cybersecurity, ethical considerations must be taken into account. Ethical AI-driven cybersecurity means ensuring cybersecurity algorithms behave in a trustworthy and fair manner. Ethical considerations in AI-driven cybersecurity can pertain to a wide array of use cases including data privacy, the responsible use of collected data, addressing algorithmic bias, developing explainable AI (XAI), ensuring these methodologies do not demonstrate more fairness over a specific group or community, and ensuring AI advocates human values. Before applying machine learning models, the knowledge of any bias it may present, and the challenge of it by amplifying signal patterns challenging this bias are essential goals to achieve. The question of fairness is therefore at the core of machine learning, data science pipelines, and data-related ethical considerations.

AI-driven cybersecurity presents several ethical challenges. The relationship between AI, machine learning algorithms, and cybersecurity is considered ethically significant in a world that is completely interwoven in the use of data, machine learning algorithms, and information communication technologies. These relationships are capable of protecting, encouraging, and strengthening security in the physical world, human rights, international peace and stability, and cyberspace. The recent grand society challenges raised above underline the urgent need for cybersecurity insurance, innovative and efficient AI technologies, their intelligent application in advanced cybersecurity solutions for smart and secure IoT ecosystems-serving compliance with existing legislative directives such as GDPR, and for the development of an internationally shared understanding of responsible behavior. According to cybersecurity, the increasingly critical and conditional role of advanced AI technologies in security is twofold. They can architecturally be designed by cybersecurity experts to protect their core systems, compartmentalized data, and intellectual property while the safe application of complex AI decision-making when invading IP and IT infrastructures of other hostile intruders is significantly raising the geopolitical stakes in future conflicts.

7. Conclusion

Despite the growing security threats, cybersecurity in the digital world has remained outdated to cope with the latest security challenges. Due to cost and resource constraints, a majority of enterprises only notify cybersecurity incidents when it is easy to detect. However, by using traditional security monitoring systems, advanced security anomalies such as unknown zero-day attacks, complicated multi-stage attacks, unauthorized insiders, industrial espionage, device hacks, etc. remain difficult to detect. We have presented a Deep Learning & blockchain-based Cybersecurity for Industrial IoT Architectural Framework. It provides much better and more efficient solutions for the IoT situations. Furthermore, it decouples these applications between devices and vertical sites, and thus greatly enhances the independence and autonomy of devices and applications.

Machine learning can oversee large numbers of diverse IoT devices in real-time and learn normal operational behaviors for those devices. However, there are challenges with the detection of cyber-attacks in IoT using ML as well. Finally, we have examined a prototype implementation and reported experimental results to demonstrate the application and effectiveness of the deep learning and blockchain-based unified security platform for addressing the security issues of the Industrial IoT. Our future work includes the practical application of the proposed framework in vertical areas of industry such as smart industrial plants, smart homes, and smart cities, assessing its performance in terms of delay, throughput, and reliability, and employing edge or fog computing to improve the efficiency of our proposed solution in detecting cyber threats of the Industrial IoT and enhancing scalability.

7.1. Future Trends

Future Trends

With an in-depth understanding of the research context, the direction and avenue planned in the future are summarized below as future trends. Primarily, the work addresses the privacy constraints using different learning worries, like federated learning, on-device learning, and homomorphic encryption. As a worker, the first researcher suggests concentrating on how to realistically change the state-of-the-art techniques. The future work will also include a huge amount of data while enhancing the performance.

In this work, the frequency patterns related to supervised learning are highlighted, displaying that the sort of attacker's control over the training dataset can influence learning.This work indicates that since the pattern detectors are used in the machine learning models, the ultimate defense is also pointed to here and the ultimate defenses also point to here before precision attacker inputs, usually by creating hard counterfactual explanations. In future work, we suggest an application of counterfactual explanations. While working on examples of attacks on a blog post classifier and a traffic classifier, the results are remarkable. Such methods can help to enhance the privacy of the machine learning system.

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