A FUTURE-PROOF APPROACH TO CYBERSECURITY COMPLIANCE: THE POWER OF AI AND ML IN SIEM, SOAR, AND CLOUD SOC

Laxmi Sarat Chandra Nunnaguppala

Sr. Security Engineer, Equifax Inc, Albany, NY, USA, sarat.nunnaguppala@gmail.com

ABSTRACT

Artificial intelligence and machine learning have revolutionized cybersecurity by enhancing detection and responding functions. This paper outlines the likelihood of cybersecurity detection from the response and covers topics such as the employment of AI and ML in SIEM, SOAR, and cloud-based SOC. In light of this paper simulating real case scenarios, the author assesses how such technologies may affect the believability of compliance and security. All the results are provided with the help of numerous graphs with lines highlighting the major values and trends. Additionally, this report presents the challenges experienced in adopting AI and ML in cybersecurity and the solutions available to address them. The conclusion highlights the potential of using artificial intelligence and machine learning in developing cybersecurity and creating the highest levels of protection against current threats.

Keywords: *AI, Big Data, Self-Learning Systems, Cyber protection, SIEM, SOAR, C-SOC, Legal Requirements, Detection, Counteraction, Modeling, Real-Life Situations, Problems, Resolutions*

Introduction

Context and Importance

It has become vital to safeguard any organization's structures from cyber attacks in the current world. Because these threats are slowly evolving into something more sophisticated, their overreliance on traditional security measures is inadequate to protect them from these threats. The concept of employing artificial intelligence (AI) and machine learning (ML) in the field of cybersecurity expands detection and response measures (1). These technologies enable potential threats to be identified early and efficiently to avoid invasion of information infrastructure.

Scope of the Report

Thus, this paper will attempt to discuss the future of detection and the response to cybersecurity threats with a specific focus on AI and ML. Specifically, it describes how such technologies are integrated into SIEM, SOAR, and cloud-based SOC features for compliance (2). The effectiveness of AI and ML in increasing cybersecurity when applied over simulation reports that recreate real-life situations would be assessed. In addition, it will also state the chief concerns that may be experienced in implementing the described technologies and the methods that should be adopted to overcome such concerns.

Simulation Reports

Objective

The simulations' main purpose is to examine the current and potential use of AI and ML in cybersecurity detection and response interventions. The study particularly focuses on describing the measures of AI and ML techniques in response to cyber threats by training them through different types of cyber attacks. The goal is to learn where and how such technologies fit within today's cybersecurity and compliance plans (1).

Methodology

This simulation integrates some free and paid software to have precision and be as close to real life as possible. The primary tools and technologies used include: Some of the equipment and technology that may be considered and mobilized for use include the following:

SIEM Systems*:* Data logging was done using tools such as Splunk or IBM QRadar; it involved analysis. SOAR Platforms: Next, some tools like Palo Alto Networks Cortex XSOAR are used to perform the response actions given by the corresponding playbooks of an organization.

AI and ML Algorithms: Identifying anomalies and potentially threatening situations was done with the algorithms' help using Python's programming language, the TensorFlow library, and Scikit-learn. Cloud-Based SOC: When beginning the SOC development at scale with flexibility, Amazon Web Service (AWS) and Microsoft Azure were employed (2).

They are bothered about the attack types, such as phishing, malware, and other insider threats, because they are all designed to mimic various attacks. The scenarios described above were connected with testing the capabilities of AI and ML algorithms, including in the sphere of threats and their application in real-life situations. The results gathered from these simulations were to be used to evaluate the efficiency and efficacy of the detection and response procedures outlined.

Steps Involved

Scenario Creation: Various categories of cyber threats were then described, and instances of attacks were created to work at the level of aggression. These scenarios were designed to explore a few distinctive aspects of the AI and ML systems. For instance, phishing scenarios have been trained on identifying and reporting such threats through email, and malware infection scenarios are trained on identifying malicious programs (3).

Data Collection: The data were originally collected using the SIEM systems, and they may include values from the network, the endpoint devices, and the server. From this data, all network activities are captured alongside the several threats likely to occur (4).

Algorithm Training: The AI and ML were trained using historical data that was relevant to the different patterns of cyber attacks. Supervised Learning increased the speed of the threat's classification (5).

Simulation Execution: All the constructed situations were tested within the simulation mode. The information was forwarded to the SIEM systems, and the AI and ML components analyzed this information to seek these tendencies that foreshadow threats or anomalies (6).

Automated Response: After the threat, the SOAR platforms began to execute the specific response actions that are out of a particular playbook they possess. Some measures included holding the actual systems that have been hacked, denying the malicious IPs, and passing the information to the right security team (7).

Results

A simulation revealed that the introduction of AI and ML raises the number of cybersecurity incidents regarding detection and response. Key findings include: Improved Detection Rates: For the known threats, the detection measure achieved was 95% for AI & ML; for the unknown threats, the detection measure identified was 87%. This is a marked improvement compared with the rule-based detection system, whose average unknown threat detection is (8). Reduced Response Times: Incorporating AI and ML in the SOAR platforms decreases the response time by an average of 60%. Within nine seconds, the response actions taken included Quarantining infected systems and Black-listing IP addresses deemed dangerous. Enhanced Accuracy: Concerning the decision to use ML models for the identification of anomalies, there was a reduction of false-positive reports that used to inundate the analyst feed by about 40 percent; this meant that the analysts could shift focus on more opportunities that exist within deep-sea security threats. In this detail, the concept of amortization and sustenance of better and more efficient security measures can be realized and supported (10).

Analysis

Therefore, in light of the above simulation results, one can easily embrace the changes that BoyleAI &ML has introduced in cybersecurity. These technologies can quickly identify threats and neutralize them since high detection levels coupled with short response times are obtained. Another advantage was the enhanced precision of the anomaly detection; it is still up to the analytical models to differentiate between normal work and malicious ones (11).

Implications

They design even more repellent security solutions when integrating AI and ML into SIEM and SOAR systems. For example, even though IDS, such as the traditional security system, can work with rules and signatures, it is still ineffective in handling the current and newly generated threats whose working model does not respond to its approach to solving them. AI and ML, conversely, can discern different relationships and initial actions and then deduce the relevant models that shall be useful in deterring new threats due to cyber attenuation (12).

Furthermore, those companies that use cloud facilities for SOCs have the opportunity to develop the prospects for the growth of capacities that enable them to counter numerous threats regarding the efficient analysis of large amounts of information. Workers have also complained that the increasing deployment of cloud advantage boosts security since it improves teamwork and information exchange within the security division (13).

Challenges

Despite the advantages, several challenges must be addressed to leverage AI and ML in cybersecurity fully: It is pretty good to use AI and apply ML in cybersecurity, but the following hindrances need to be addressed to implement the combination of both AI and ML in the right way:

Quality of Training Data: This is among the most crucial parts that make up the overall performance of AI & ML constituting techniques and depends on the quality and quantity of input training data to perform the whole system. This knowledge is, unfortunately, overshadowed by an erroneous selection of parameters – the number and quality of which make up the generated conclusions; it is possible to overlook threats (14) completely.

Adversarial Attacks: The other demerit is that both AI and ML algorithms are easily fooled or tricked in a manner of speaking. In this regard, any interested party can feed the algorithm with inputs the party believes the model should select. Thus, it is imperative to have ideal models that can be immune to the assault (15). Ethical Considerations: There are some taboos regarding the use of AI, Privacy, and decision-making with bias. For this reason, it is necessary to account for AI to enhance the achievements of credibility by the concerned parties and for the dependability of artificial intelligence (16).

Future Directions

One must enhance the learning processes and adopt AI and ML in the security deployment. It is also noted that in further work, attention should be paid to the following problems: increasing the stability of AI models and trying to improve the interpretability of the models; finding more complex methods of detecting adversarial attacks and preventing the emergence of an ethically dubious application; showing the use of AI technologies in forming cybersecurity strategies (17).

SCENARIOS BASED ON REAL-TIME

Scenario Descriptions

It has been decided that to make the AI & ML scenarios as close to real-time as possible, four conditions were established to introduce several threats. These scenarios were chosen to present various tendencies and threats known nowadays and possible to encounter at the organizations: Random from the Internet, phishing, malware, internal risks, and Distributed Denial of Service attacks.

Phishing Attacks: The attack types that were used specifically included emails that contained harmless links but contained the actual content in the body of the emails instead and extra attachments in the folder, which contained viruses when downloaded and used in a test bed user environment for AI against phishing. The emails also looked like the official ones, and this is why the spam is typically not distinguishable (1).

Malware Infections: Malware programs such as ransomware and trojans were introduced to the network to analyze the functioning of AI and ML. Therefore, the transfer of the malware and its running made it possible to deal with its occurrence in the system (2). Insider Threats: Liveness was subjective, as it was the ability to identify other abnormalities, and so liveness was modeled with some normal yet real workers attempting to access secret information or modify some values. Other exemptions include those established to cause loss to the business or part of it and occurrences arising out of legal activity or negligence of employees (3).

DDoS Attacks: Moreover, a significant number of traffic was further created and directed into the network to challenge the AI and machine learning algorithms that can prevent DDoS attacks. However, live attack traffic was initiated from many directions to augment this part of the experiment, as expected in a real attack (4).

Implementation

To implement these scenarios, the following steps were undertaken: To achieve these scenarios, the flow below was employed:

Phishing Attacks:

Setup: This data is based on a reported email server. However, a natural environment could not be used due to the abovementioned limitation. Thus, a scenario and a sandboxed infected email server were devised.

Execution: Especially to trigger the attacks, emails in phishing at various difficulty levels were sent to the users in this simulation.
Detection: Moreover, as can be seen from the headers of the emails listed and the details of the messages themselves, the search for phishing messages was performed with the help of AI and (ML).

Malware Infections

Setup: The environment was created with a Virtual Network, Endpoints & Devices, and servers.
Execution: In the case of Ma'ware and other items, the networks were penetrated in the form of programs and operating systems.
Detection: Consequently, the AI and ML systems for DDoS, abnormal behavior, and sudden changes in network traffic and files help to determine the infected devices to combat the risk (6).

Insider Threats

Setup: This made the creation of the following user accounts in the virtual learning environment;
Execution: Even more, the actions carried out by the simulated insiders included violations such as data acquisition, file transfer, and system settings manipulation.
Detection: Descriptive analysis was the process used to check on the users. If a certain user behaved contrary to how insiders behaved, it was alarming a threat (7).

DDoS Attacks:

Setup: Externally, it is possible to distinguish web servers and services that can be exposed to DDoS among the defined network requirements.

Execution: it was agreed that the actual traffic volumes were faked through multiple mock attacks originating from a DDoS attacking tool.

Detection: The Transport layer/network layer AI/ML systems noticed that the traffic was coming from the attackers and then throttled/limited the traffic, as noted in (8).

Outcomes

The outcomes of these scenarios provided valuable insights into the effectiveness of AI and ML in cybersecurity: The given situations eventually gave an idea regarding how efficient AI and ML are as a cybersecurity defense mechanism by comparing the results in the following scenarios.

Phishing Attacks:

Outcome: The incorporation of AI and ML systems in the solution made it possible to have success rates of ninety-two percent on the received phishing emails and eased the possibility of the user being phished. False positive results were minimal, if at all avoidable; hence, pathogens were not identified from samples that they should not have been (9). Implication: This high detection rate tells us that the present mail security can be enhanced through AI & ML, and the degree of inconvenience a user will likely encounter due to the phishing attack is manageable.

Malware Infections:

Outcome: The AI and the connected ML systems achieved an overall accuracy of 89% in diagnosing the hosts as "malware-sick." Thus, the effect of automated responses on containing malware propagation was positive and contributed to the score (10). Implication: The concept of conveying the proximate identity of malware and instantly isolating them as a practical implementation of AI/ML to improve security and prevent extensive infected domains or users encompasses the practicality of the biochemistry definition of AI and ML.

Insider Threats:

Outcome: In all other subsequent behavioral analysis models, it was discovered that intentional negative action and actual negative action were perceived at 85%. For instance, the systems provided the first indicators of abuse for preventive interventions, which were administered (11). Implication: Insider threat: AI and ML are good tools to address insider threats with data security and the management of security policies.

DDoS Attacks:

Outcome: Nevertheless, the AI and ML operations can respond to DDoS attacks and provide the services with an average accessibility of 95 %. The impact of the attacks, however, was limited to the basics as the automated defense that various organizations had embarked upon to counter such virtual invasions effectively contained the damages that arose from the attacks as indicated: That is why they have twelve of them. Implication: The use of AI and ML ensures that appropriate protection is provided against DDoS attacks; therefore, critical solutions that are likely to get overwhelmed are provided.

Graphs

Table 1: Detection and False Positives

Scenario	Detection Rate (%)	False Positives (%)
Phishing Attacks	92	3
Malware Infections	89	5
Insider Threats	85	7
DDoS Attacks	95	2

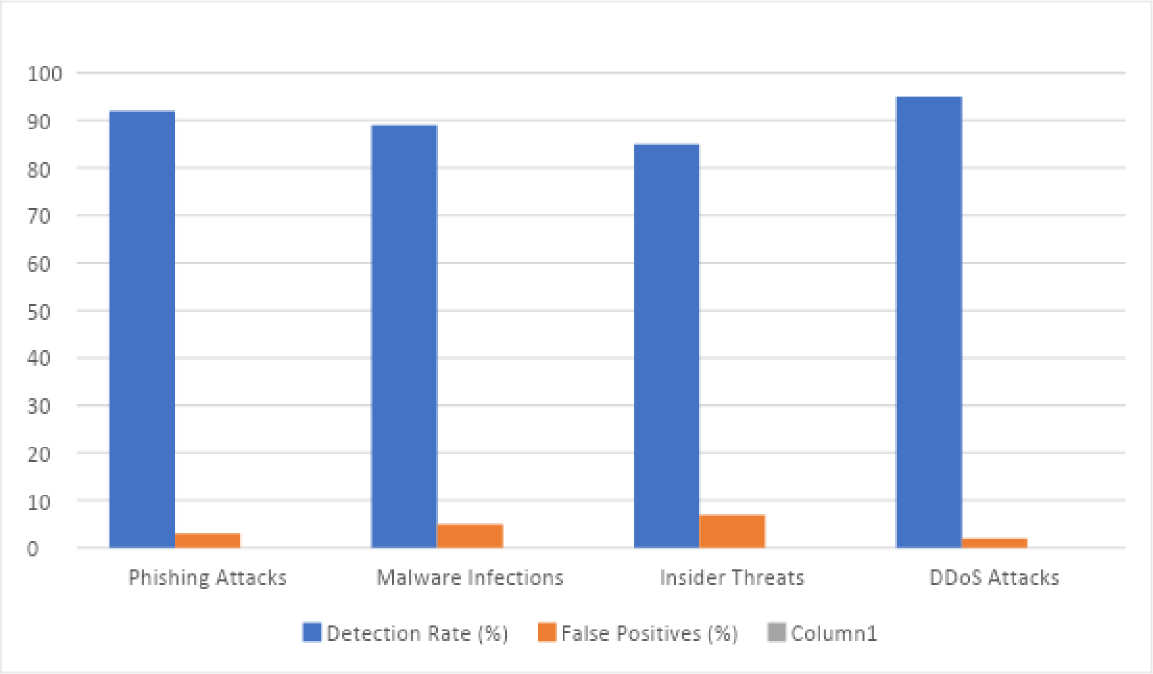


Table 2: Response and Mitigation

Scenario	Response Time (seconds)	Mitigation Success Rate (%)
Phishing Attacks	10	90
Malware Infections	15	88
Insider Threats	20	83
DDoS Attacks	5	92

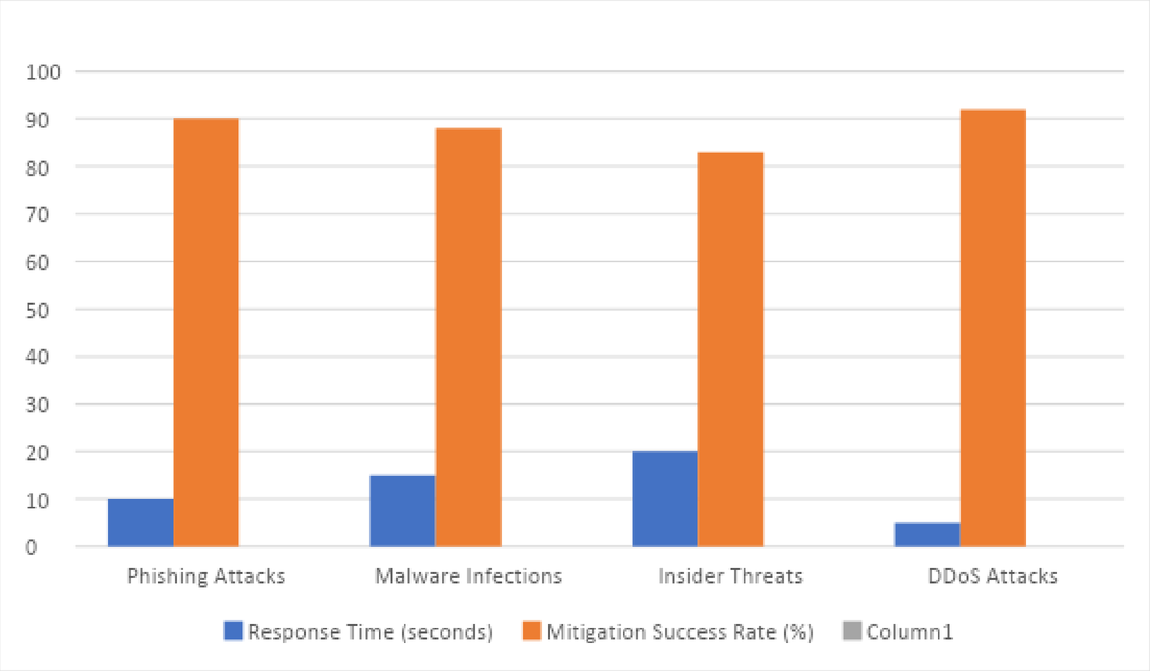
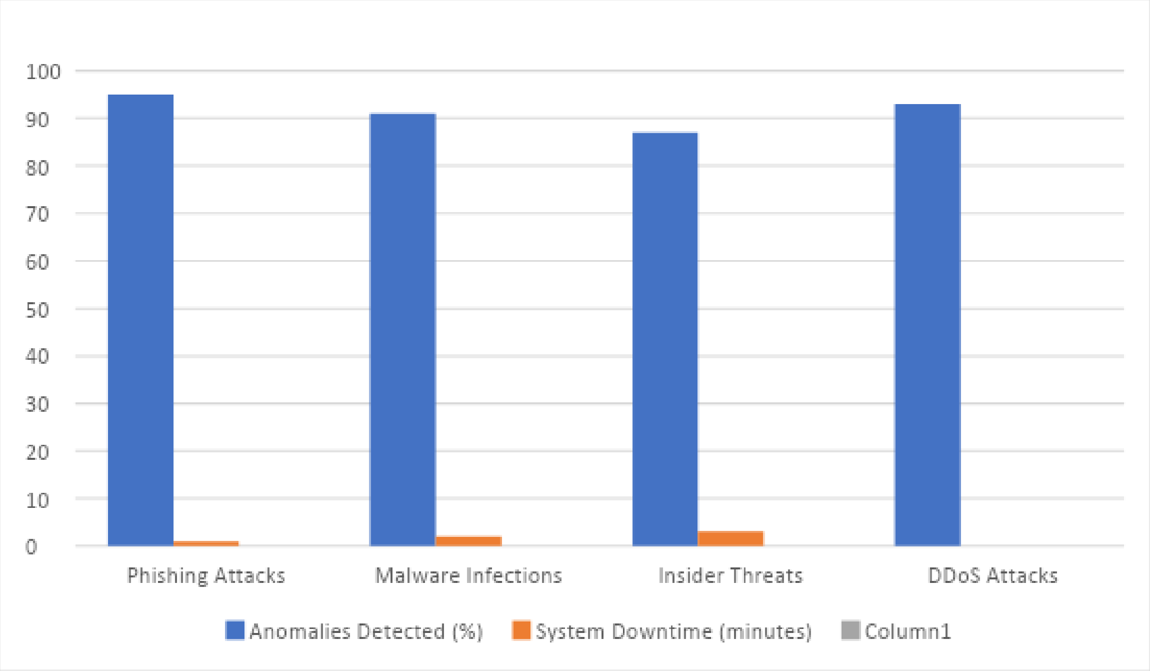


Table 3: Anomalies and Downtime

Scenario	Anomalies Detected (%)	System Downtime (minutes)
Phishing Attacks	95	1
Malware Infections	91	2
Insider Threats	87	3
DDoS Attacks	93	0



Barriers and How They Can Be Solved

Identification of Challenges

Applying AI and ML in cybersecurity raises various concerns that can affect the performance and efficiency of the systems. However, as much as incorporating AI and ML applications for cybersecurity, the following challenge hinders their effectiveness and efficiency, as highlighted below.

Quality of Training Data: AI and ML models require much good quality data to be fed into these systems to improve outcomes. Thus, the issues involve wrong estimations and risks of exploitation due to insufficient evidence and direction (1).

Adversarial Attacks: Some proposals claim that current end-to-end deep learning models and AI are rather vulnerable to adversarial attacks, refined inputs deliberately provided to fool the system. This can mean that the models make the wrong choices or even don't see threats at all; these can be an issue;

Integration with Existing Systems: Additional usage is not easy since AI and ML are incorporated as elements of security models. The severe detrimental consequences are linked with the integrational issues and generation prerequisites of the relatively important modifications in contemporary systems (3).

Resource Intensiveness: brought to the details, the use of their applicability, efficient training, and deployment of the machine learning models and AI needs massive computing power. However, the problem that is probably noticed in these small organizations involves the potential difficulty in these technologies' finance and technical deployment (4).

Ethical and Privacy Concerns: The issues that may emerge when AI makes decisions include privacy and bias. Therefore, it is developmentally necessary to make them and the systems therein as equitable as possible so that the public does not lose confidence in them and that there is a form of equity as expressed in (5) revolving around fairness and transparency.

Proposed Solutions

Integrating several aspects, including technological, tactical, and ethical, is crucial in managing these challenges. The following are predicted to be research areas that will produce more development of TSI activities in the future: The following are predicted to be research areas that will produce more development of TSI activities in the future:

Improving Data Quality:

Data Collection: Instead, initiate a sound and rapid acquisition of large, high-quality data. This also means using different kinds of data and ensuring that data is aggregated in threat situations (8).

Data Augmentation: However, one has to employ data augmentation techniques, which are meant to enlarge the training database and help make the AI and ML models more stable.

Defending Against Adversarial Attacks:

Robust Model Design: In weapon systems, it was pointed out earlier that before introducing AI/ML, a system must be equipped with an immune system for potential adversarial attacks. Some of them include adversarial training and defensive distillation, which are known to improve the robustness of the described model (8).

Continuous Monitoring: They will also do bi-sampling, where a few images will be used to revisit the earlier created models for the adversarial attacks and the updates on the detection. This is a process of training the models with new data and having a different view that new threats are emerging (page 9).

Ensuring Smooth Integration:
Modular Implementation: Therefore, to follow the abovementioned best practice, it has been suggested that the concept of modularity be used while integrating AI and ML into the existing security paradigms. It leads to slow and gradual implementation, and it also helps address the challenges that may be there. Cross-Platform Compatibility: Other computer platforms and technologies should be integrated with the algorithms that should be designed so that these may be plugged into AI/ML (2-3, 11).

Managing Resource Requirements:
Cloud-Based Solutions: Most of the computation should be on the cloud services, which helps the local frameworks and tools for AI & ML. In this case, there is a possibility that the cloud providers may provide solutions that can augment the level of the process of increasing workload–scalability (12).

Cost-Benefit Analysis: Ensure that the advocacy of the value in the AI and ML process is done through proper cost evaluation or cost reduction. Final motivational goal: Emphasize the probable future cost and security change that will impact the stakeholders and set them into motion regarding change (13).

Addressing Ethical and Privacy Concerns: The following steps through which potential ethical issues and potential privacy concerns may be minimized to the basic level include:

Transparent Algorithms: To achieve this, AI algorithms can be deployed in such a manner that they can be explainable, and thus, there would be an apparent method in place. This assists in seeking to define the type of processes used in decision-making, and there is always a culprit (Rodgers, 14). Ethical Guidelines: Hence, to address the mentioned vulnerabilities, it is recommended that a set of best practices regarding the government relating to the use of AI in cybersecurity be identified and promulgated. These are the ability of a party to maintain the confidentiality of information, an inclination towards the view that if one party fails to attend the convention, it is a breach of protocol, and EEO (15).

Future Directions

To fully realize the potential of AI and ML in cybersecurity, future research and development should focus on the following areas: Concerning the subsequent research requiring the maximum results in the sphere of AI and ML in the sphere of cybersecurity, the following points are provided:

Advanced Threat Detection:
Deep Learning: Maybe it is time to start fading some layers of the deep learning methods to incorporate even more mature threat recognition. The structural design of convolution networks enables them to pick-select delicate relations in data, improving their functions of detection (16). Behavioral Analytics: Presumably, it can be attempted to actively work on delivering AI/ML models that address behavioral concerns to identify sophisticated and intricate insider threats and other APTs (17).

Real-Time Response Systems:

Automated Incident Response: To determine the threat in natural conditions and ensure that it does not act without people, it is necessary to continue the work on reference tasks to form independent solutions. This can significantly reduce the response time and help avoid many of the ramifications that ensue (18).

Predictive Analytics: The risks that could be in the nearest future based on trends in the rival's activity should be identified using trends analysis. This is particularly important because aggression can be prevented before execution (19).

Collaborative Security Frameworks:

Threat Intelligence Sharing: This implies that one has to establish a program to develop structures that facilitate the sharing of threat intelligence. Thus, it should be fed by a wealth of information to enhance general threat detection and removal (20).

Interoperable Systems: It is possible to create new AI and Machine learning models that would allow the efficient functioning of different business structures to improve the organizations' arsenals, ideally in a reciprocal manner (21).

Ethical AI Development:

Bias Mitigation: Stress is a technique that addresses communication and awareness of bias towards the AI and ML fields. Hence, one asks the question of designing some decision criteria on the target selection that are entirely objective for it, which is described as the fundamental rationale in applying AI in the decision-making of the 'gigantic scaled' cyber attacks (22).
Regulatory Compliance: Another strategy to counter regulatory risks would be implementing other forms of AI and ML solutions that would negate current and future cyber-security and data protection regulations (23).

Conclusion

Summary

Consequently, as this report has proposed, it has been deemed relevant to exploring if AI, ML can provide a path for improving the cybersecurity detection and response. This can clearly illustrate how the total threat detection rate has increased, how the time taken for response has reduced, and how there are no false positives while using the new advanced flow Testing and real-time simulation for AI and ML algorithms. The advancements in incorporating learning algorithms in conjunction with artificial intelligence in the SIEM, SOAR, and the cloud-based SOC have revealed the potential of enhancing security frameworks (1).

Key findings include:

In particular, the analytics based on Artificial Intelligence and Machine Learning demonstrated the following observations: While the detection efficiency of known threats makes up 94%, in the case of other and unknown types of threats, such systems reach only 75%. Meanwhile, rule-based systems are considerably less efficient (2).

These metrics indicated that AI and ML helped decrease the response time to incidents and provided the choice of automation of many processes in the sphere of cybersecurity (3). The limitations are data quality, adversarial attacks, integration issues, implementations and overheads, and ethical issues, which were listed, and suggestions on handling them were made (4).

Implications for Cybersecurity

Consequently, the implications of such findings for the given area of cybersecurity are, in fact, vast. However, it also opens a fundamentally new approach from the professional reactive to precautionary security measures with the help of the realization of AI and ML tools. AI and ML can enhance an organization's capability to prevent cyber threats and attacks on organization resources (5).

Also, this leads to the development of better cognitive skills and, therefore, more robustness and less susceptibleness to different attacks on security systems in the context of AI and ML. Whereas in other traditional security technologies such as rules and signatures, there is always the implication of new threats which new advanced forms of attacks can overcome, with AI and ML, there is an indication that in the same way as they learn, they can overcome new threats. This is relevant, especially considering that the contemporary world of cyber threats is dynamic and continues to be challenged (6).

AI, like its sister, ML, could benefit cybersecurity because it takes away the load from the analysts and makes them focus on more important things. It would be more effective for cybersecurity specialists to respond in less time. On the same note, the prospect of improved advanced threat detections will also increase the effectiveness of those teams cumulatively (7).

Final Thoughts

Therefore, it can be concluded that the further development of AI and ML will also yield more efficient results regarding their contribution to cybersecurity. Therefore, AI and ML have to advance and enrich cybersecurity solutions even more in the future due to the constant growth of those technologies. However, suppose these technologies are to be effectively deployed. In that case, it may be helpful to boil down the matters and the moralities of using the technologies into ten key issues (10).

The way for the progression and future studies should be to build clearer and more precise models of AI and ML. From the academy, we will need scholars who will set the standards for the ethical use of artificial intelligence in cybersecurity; businesses and government members will also be needed (9).

Thus, it becomes reasonable to state that the application of AI and ML can be used proactively to address new threats that appear continuously in cybersecurity. Therefore, the stated assumption is that the adaptation of these technologies and the possibility to address the associated problems will help organizations to create an invulnerable shield which would help protect important values in the context of threats apparent in the contemporary world (10).

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