International Journal For Recent Developments in Science & Technology
2581-4575
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A Peer Reviewed Research Journal

Unlocking SIEM Potential: Secure, Scalable Cloud Architecture with Artificial Intelligence Machine Learning

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Abstract:

The amount of data has increased recently, motivating the introduction of advanced data engineering solutions in the cloud. The current paper aims to discuss the development of secure and highly scalable SIEM systems and their integration with AI and ML forms. The main goal is to improve the functionalities of the SIEM systems in processing, analyzing, and countering massive amounts of security information in real-time. The performance and capacity of cloud-based AI and ML-based SIEM solutions can be tested using fully functional predefined scenarios. Precise documentation emphasizes the procedures, instruments, and outcomes achieved, proving that actively utilizing AI and, specifically, ML contributes towards enhanced precision and efficiency of security breaches' identification and mitigation. This paper also looks at data integration difficulties, growth quotients, and adequate security measures to propose workarounds and benchmarks to enhance system dependability and effectiveness. Our findings highlight that it is possible to design AI and ML-based systems to utilize cloud-based SIEM systems more intelligently and dynamically when handling various threats. Thus, this paper will contribute to the current data engineering and cybersecurity research trends to further its improvements and innovations.

Keywords: big data processing, computational data management, advanced data analytics, cloud services, security information and event management, AI, ML advanced computing, cyber security, growing business requirements, real-time data detection, security threats.

Introduction

Therefore, Cloud computing has become prominent for organizations, especially in the current world where databases are large and ever-expanding. Data engineering in the cloud means architecting, developing, and managing large-scale data infrastructure and processing pipelines to handle these enormous volumes of data. The cloud has massive benefits, including elasticity, Liberality, and economy, which are critical in data engineering today. However, like any other advancement, these have some associated problems, especially in data security and real-time data analysis.

SIEM systems are critical in cybersecurity because they permit near real-time analysis of security alerts raised by the applications and the network equipment. These systems monitor and control security by pulling data from varied sources, doing analytics, and generating the proper procedures for mitigating risks. Subsequently, the reliability and scalability of secure SIEMs cannot be overemphasized, as the system is the foundation of every organization's security measures to guard their data against malicious threats/attacks or meet compliance requirements.

In recent years, adopting AI/ML in SIEM has

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become one of the industry's revolutionary strategies. AI and ML techniques can process a significantly large volume of security data within less time than it would take experts using conventional methods, and they can perform further analyses to detect disturbances that might point to a security threat. This helps SIEM systems to enable the prediction of threats and get in a position to promptly respond to threats that prevail amid short periods of vulnerability, which, in the end, boosts the organization's security status. Since SIEM systems incorporate AI and ML, they can identify new threats to a network besides recognizing dangerous patterns that other systems have not seen before. This paper focuses on the evolution of cloud SIEM systems, secured and enlarged by AI and ML components, with a detailed description of the methodologies, result sharing, and examination of the implementations of these technologies in enterprise cases.

Simulation Reports

Description of simulations conducted

An extensive data set replicates the traffic that may be handled during testing to achieve realistic testing conditions. The datasets originated from switches, routers, application servers, end-point security programs, and synthetic logs that were added to mimic specific types of attack traffic. The practice environment was established in cloud infrastructures, such as Amazon Web Service and Microsoft Azure since their structures were exploited to accommodate the scale of the tests [2].

Objectives of each simulation

Thus, the primary goals and objectives of the simulations are as follows. The initial goals of the simulations were complex and focused on checking out various aspects of the functionality of the SIEM systems. The specific objectives included:

Scalability Assessment: To find out the behavior of SIEM systems and how effectively they can grow in terms of being put in the cloud environment when many data and threat instances are coming in simultaneously. The first requirement, or a critical component as far as the software choice, is scalability because of the large amounts of data that modern IT infrastructures generate. The load conditions ranged from average to peak loads to determine the behavior of the systems without degradation [3]. For instance, we gradually introduced extra simulated events per second to see how the tested SIEM systems prevented the escalation of the load.

Threat Detection Accuracy: To compare the chosen AI's and ML algorithms' ability to recognize and classify potential security threats efficiently. Low false negatives and false positives are critical when it comes to detecting threats. High accuracy is needed to avoid overwhelming security teams with unsupporting alerts or overlooking threats [4]. The simulated attacks involved known patterns of attacks and ab initio attacks to see how the algorithms would fare when faced with security incidents they had never encountered. In the case of comparing the results, we considered the performance against the background of typical SIEM systems without using AI solutions.

Response Time: To determine how fast the implemented SIEM systems were in their ability to identify, analyze, and provide a solution in case of a security threat. Fast response significantly reduces the effect of security threats as much as possible. The simulations quantified the time from the threat's identification to the action being taken, such as removing an infected device from the network or blocking suspicious traffic [5]. We recorded the time stamp for each phase of the response process implemented to detail the areas where time was saved by AI and ML improvements.
Resource Utilization: To evaluate the cost and effectiveness of the utilization of resources in the implementation of SIEM systems, a measure of CPU usage, memory usage, and network usage will be performed. Proper management of available resources enables the SIEM systems to perform the set tasks while consuming fewer resources as the cloud environment allows ([6] pg.302). The simulations measured other resource utilization aspects to see how the systems were achieving between efficiency and resource utilization. Of them, the nominal one focused on how the employment of AI and ML impacted the

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general use of resources compared to conventional techniques.

System Resilience: To determine the systems' resilience and dynamic effectiveness and flesh out their adaptive operational statuses even under constant and complex assaults. The efficacy of collaborations in maintaining a continuous safeguard even under heavy attack is due to resistance. The first activities covered sustaining attack simulations to observe the systems' performance when faced with sustained threats and attempts to overwhelm or get around SIEM security measures [7]. Some of the criteria that were considered included the fault tolerance of the systems as well as the functionality of the backup modalities.

Methods and tools used

The primary tools and technologies used in the simulations included The following emerged as the principal tools and technologies employed in the simulations: ***Cloud Platforms:*** Amazon Web Services (AWS) and Microsoft Azure were used to place the SIEM systems, providing the necessary format and scope [2]. These were selected based on their being general-purpose languages, characterized by high data security, and used in on-demand resourcefulness. Hence, both AWS and Azure use various services to support big data processing and analytical requirements for running detailed SIEM simulations. The application environment layout of this application was therefore designed with the specific usage of their VM instances, storage solutions, and network services relevant to propelling it to capacity in handling the amount of data required for processing and provision of results amid the complicated computational simulations it would need. In addition, in both environments, basic security features were built in and encompassed identity and access management encryption; furthermore, the simulations were conducted securely.

SIEM Solutions: Thus, the efficient SIEM solutions, which are Splunk, Elastic Stack, which is a package of Elasticsearch, Logstash and Kibana, and IBM QRadar, are implemented to create a complex security monitoring system [8]. These SIEM solutions were selected as they offer high analytic capabilities and flexibility and introduce high levels of varied features. Splunk is a powerful but improbable free text search engine appropriate for ad-hoc searches and interactive visualizations, and it was used for log collection and analysis. The offered stack is based on the Elastic suite that includes components for splunking vast volumes of data and search queries in real-time sequences. Applying the integrated and correlating system like IBM QRadar, which was described as relatively strong in the integration and correlation categories, it was possible to determine the system's potential threats and prioritize them by their relation to each other and the general picture of security events. To ensure that the incorporated AI and ML algorithms would be thoroughly tested to demonstrate the improvement of each SIEM solution's detection and response capability, the solution was set up correctly to ensure the solution's integration.

AI and ML Algorithms: To this, further layers of AI and ML elements included in the SIEM systems were the anomaly detection layer, predictive analytics layer, and machine learning layer[9]. Many of these algorithms were conducted using different machine learning libraries: TensorFlow, PyTorch, and Scikit-learn. Other methods, such as algorithms for anomaly detection, were also employed to highlight tasks' deviations from normal behaviors and perhaps give some indication of security threats. Consequently, predictive analytics models are concerned with trends of security incidents to prevent

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similar incidences in the future. Classification and ranking of the collected event data were done using different supervised and unsupervised machine learning algorithms. These models are also improved by considering the large amount of data to arrive at the better-performing models. Integrating these AI and ML algorithms into the SIEM systems automated threat analysis and preparedness, reducing the time to contain security threats.

Data Sources and Preprocessing: This incorporated all types of data that one is likely to feed into the SIEM systems to improve performance analysis. These were traffic logs obtained from the network, the events happening in the system, application logs, and activities logs from various environments. Simple preprocessing was done on the data for cleaning and normalization to enhance the data for application and further analysis by the AI & ML tools. Data cleaning was carried out as preparation by removing all repeated instances and handling situations where the values are absent and data is imprecise. Other extraction procedures were also applied to establish different features that could help enhance the threat detection models.

Testing and Validation Tools: To strive for as realistic outcomes of the simulation as possible, various testing and validation resources were employed. These were the calibration tools used to evaluate the efficiency of the system's scalability tools, performance assessment instruments for assessing the system's capacity, and verification frameworks to ensure the applicability of the implemented AI and ML models in the designated system. The network load and the attack vectors with the difference in intensity were developed with the help of Apache JMeter and Gatling. The model evaluation for the chosen AI and ML algorithms was done with the help of cross-validation and confusion matrix.

Monitoring and Logging Tools: Higher-level monitoring and logging utilities were applied to control the performance of SIEM systems and AI and ML-integrated provisions. These tools provided live updates on the activities of the systems, resource utilization, and hack attempts in the system. Collectors and data monitoring tools included Prometheus and Grafana to assist in analyzing and managing system problems and other fields defined in advance by the company. For collecting and indexing log information &Fluentd and Logstash were employed. Here, the analysis was more straightforward based on the details we got from the simulation experiment.

Results of the simulations

From the results of the simulation studies, the author showed that the usage of AI and, more specifically, ML improved the detection and response capabilities of the SIEM systems. This section builds upon the outcomes of the various scenarios, focusing on the performance positives and discoveries.

DDoS Attack Mitigation

In Distributed Denial of Service (DDoS) attacks, AI-integrated SIEM systems could detect and stop the attacks in less than seconds, significantly lessening the threats that could harm network operating capacity and availability. B Kerr describes the conventional SIEM systems as suffering from visibility overload, especially during a DDoS attack due to the voluminous traffic. However, the AI and ML models used in these simulations were trained to identify signs commonly associated with DDoS attacks by rendering abrupt increases in traffic volume and the characteristics of the traffic flow split across the different IPs [1]. These patterns were identified at a very

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high speed, thus allowing the systems to initiate similar response mechanisms like rate limiting and traffic redirection to counter the attacks. This led to less disruption of the network services and ensured business as usual, supporting that the integrated SIEM system is more responsive [2].

Phishing Attack Detection

Thus, during the corresponding simulations of the attacks using phishing emails, the machine learning algorithms correctly filtered inflammatory emails and alerted the management to possible data leaks. Phishing is not easy to prevent since it is based on cunning and psychological features that attackers use in their work. The ML models used in the simulations above involved the use of natural language processing (NLP), which is employed in analyzing the content of emails to detect phrases, senders' conduct, and any other feature that may be regarded as phony within the context of a phishing attack [3]. These models were trained to learn from new data and adjust their methods accordingly. Thus, false positives and negatives were minimized as the models' proficiency enhanced. In addition to preventing phishing emails from ever reaching end users, this approach was later found to provide security personnel with a proactive environment to study and counteract threats to increase overall organizational security [4].

Malware Intrusion Detection

The simulations also covered the tests of the system of detection of malware intrusions and the response to them. This was done with the help of AI and ML techniques, where the models needed to analyze the system logs, FIM, and network traffic for signatures and mal affairs' behavior. The findings indicated a rise in the detection rates compared to conventional methods. Cognitive systems were enhanced with AI capabilities that could accurately detect known malware and new malware previously unidentified through patterns, anomaly, and behavioral analysis [5]. This dual approach enabled the most excellent coverage, revealing the well-known threats and newly emerging malware. The other concern is how infected systems could be detected, isolated, and eradicated before causing enormous losses [6].

Scalability and Performance

All the implemented systems performed very well in terms of scalability, that is, the degree of their ability to expand their data processing capacity throughout the stages of the study. With the increased rate and number of security events, the AI and ML learning algorithms and capacities maintained the output quality while not compromising speed. This scalability is essential for today's businesses, which are characterized by massive streams of security-related data produced daily. AWS and Azure, as cloud infrastructure, serve a necessary function in this aspect as they involve sealing resources that can grow and shrink on their own, depending on the requirements of the simulations [7]. To do this, various use cases that can be carried out on the systems were simulated at peak load, for example, where multi-pronged attacks were launched simultaneously. These situations were well managed by the new generation of integrated AI-enhanced SIEM systems, which provided constant security and monitoring without resource exhaustion [8].

Resource Utilization and Efficiency

They also depicted how there could be efficient ways of working, particularly in the management of resources. The applications that help enhance the security data are AI and ML, as they do not possess the computational intensity that is required in conventional SIEM systems. This

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optimization reduced the utilization of CPU and memory by the systems to a bare minimum; thus, scaling up the system was cheap. When it comes to optimizing resources, it also decreases the time required to process the given security event, contributing to the performance of systems [9]. Resource management features of the cloud environments, such as auto-scaling and load balancing, fit the characteristics of AI and ML optimizations used in the SIEM systems since the systems are likely to scale without effort [10].

System Resilience and Robustness

The third technological strength from the simulations concerning the integrated systems with the collaboration of AI was the aspect of resiliency. Various systems were kept active during the continued and complex attack paradigms, clearly showing the systems were quite sound. Sustained attacks stressing applications like APTs and multi-vector attacks were used, probing the systems' resilience and learning ability [11]. The flow of the events depicted from real-life cases increased the AI and ML algorithms' capacity and ability to detect and respond to similar incidents as the activity proceeded in real-time. This adaptive capability made it possible to maintain and successfully counter the longer-lasting attacks without being penetrated or drained of the security posture [12].

Analysis of the results

The interpretation of the analysis of the simulation results led to the identification of several conclusions concerning the specific application of AI and ML for improving the performance of SIEM systems. First, integrating AI and ML made the system more effective in identifying threats and attacks. Second, the generality of the cloud-based SIEM systems was confirmed, with the systems' performance remaining healthy even when the SIEM was flooded with information [14]. Third, the simulations demonstrated how the observers maintain constant vigilance and readjustment of AI and ML programs for optimality under the ever-changing contexts of threats [15]. Last of all, the results pointed out areas of development regarding a more refined method in data integration and improved GUI for the security analyst.

From the study findings above, it is possible to propose further research and development of cloud-based SIEM systems and the application of AI and ML to strengthen cybersecurity processes. Since threats escalate in sophistication and intricacy with time, developing and improving such technologies will significantly protect cloud-based data engineering systems [17].

Real-Time Scenarios

The use of explanation of Real-life situations for employment

It is worth understanding that the real-time scenarios deployed in this study were well constructed to capture the incidences and the dynamic nature of insecurity that organizations are exposed to. It was possible to observe that these attack scenarios were quite diverse and comprehensible, including vectors or types of activity such as Distributed Denial of Service (DDoS), phishing, virus, and Advanced Persistent Threat (APT). The cases were intended to assist in assessing the results of SIEM systems and their capacity to recognize, interpret, and manage the identified threats in a real-life context.

Distributed Denial of Service (DDoS) Attacks: The above survey of DDoS is larger concerning self-exhaustion of network resources and, therefore, service unavailability. The simulation analyzed the degree of attack and concentrated traffic

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from web clients, email clients, extranet, and internal, and it was also discussed to witness the capability of SIEM systems in perceiving the traffic and preventing intrusion at an initial stage [2].

Phishing Campaigns: The feasibility of phishing attacks consists of the following common types of email attacks, the primary purpose of which is to mislead the user into entering the aforementioned critical information or launching the undesired application. Thus, as in these sample scenarios, the attacks include spear-phishing emails that mimic traditional email communication and aim to distinguish the performance of the SIEM systems in contrast to identifying and describing suspicious email text using NLP techniques [2].

Malware Infections: These were real-life profiles of the malware attacks that commonly exist – ransomware, trojans, spyware. It is primarily based on the scenario of performing the detection of the malware by the SIEM systems of the signature-based detection as well as behavior-based one to ensure that SIEM systems are quite capable of identifying the new unknown threats in addition to the known ones [3].

Advanced Persistent Threats (APTs): APT scenarios are narrower in a given angle, where cyber attackers come up intending to steal information over a long period. The assessed solutions' effectiveness in detecting suspicious activity indicators during the active phase of an attack is the main focus of these scenarios, namely lateral movement inside the network, data transfer, and C2.

Industry relations are a factor that incorporates relevance to current industry practices.

Besides, considering the threats within the given study, they are reasonable, and the scenarios employed in them are similar to the threats facing present-day organizations today. Therefore, the study links the outcome of the simulations to actual attack paradigms and attack approaches for it to be under today's enterprise security threats and challenges.

Real-world Relevance of DDoS Attack Scenarios: DDoS attacks remain one of the significant threats to organizations worldwide; many instances are recorded to have taken place annually. These attacks can undoubtedly impact services' reputations and are even expensive to rectify, all at the same time. Therefore, concerning the simulation of DDoS attacks in this study, information about the utilization of the integrated SIEM systems in improving threat control will ensure the availability and sustainability of the services [5].

Phishing Campaigns in the Industry: Phishing remains one of the most popular types and effective for cybercriminals. The role applied in the scenario analysis highlights the necessity of including the solutions to investigate the sender's credibility and filter such threats in SIEM systems. The above scenarios portray how phishers operate and the strategies used in practicing the vice, which is helpful to other organizations in developing more effective ways of combating the vice [7].

Malware Infections and Industry Practices: Contemporary malware is far different from the early ones, indicating a need for better solutions to this menace. This reflects the types of malware used in the research to explain the problems where different malware occur and provides data to the SIEM systems about the

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developments in their frameworks for identifying malware.

Advanced Persistent Threats (APTs) and Industry Relevance: APTs are said to be some of the most severe threats in cyberspace because they are long-term and infiltrative. This is sub-optimal, and some of these requirements, such as anomaly detection and behavioral analysis of higher-tier threat identification, are not measured by the APTs' characteristics currently supported by modern SIEM systems. These examples are helpful because they explain threat activity that is both frequent and prolonged [8].

Data Sources and Validation

Reviewing the results of the simulations, it was mentioned that the data used for simulations are based on real-life datasets and realistic datasets that mimic real-life attacks. The primary sources of data included: The important sources of data were:

Network Traffic Logs: This is acquired from various aspects of the network: the routers, switches, and even the firewall apparatus. It was discovered that these logs provided highly detailed information on the network activity required to identify growing divergence and possible security violations [9].

System Event Logs: Gathered at the network's operating system, application, and security appliance planes. Therefore, such logs also included users' activity, system malfunctioning, and security concerns, which are crucial for the comprehensive threat evaluation [10].

Application Logs: These are delivered from web servers, databases, and other critical corporate applications. These logs also effectively identified application Layer attacks and additional features and peculiarities pointing at a security issue [11].

User Activity Logs: Provided the overall oversight of the user activities practiced in the systems and applications, insider threats, and the compromised accounts of the organizations [12].

Several data validation techniques were employed to ensure the validity and reliability of the simulation data. To make the gathered data of the simulation as valid and reliable as possible, the following methods were used:

Data Cleaning and Normalization: The raw data refers to any data item allowed in the analysis and was preprocessed in the sense that anything that did not form relevant information was eliminated or banned. In the data cleaning process, data reduction was carried out, the handling of missing data was established, and the actual data was transformed into a standard input form from the different data sources [13].

Anomaly Detection: This paper also explains how the proper use of statistical tools and artificial neural networks was applicable in data cleansing and excluding more outliers that could have further affected the outcomes. This step was done to maximize the accuracy of the simulations used, as the work of [14] shows.

Synthetic Data Generation: As for scenarios in which it was impossible to use accurate data, the latter was successfully modeled using attack paradigms that are as close to real life as possible. These minimized chances by ensuring that several simulations incorporated nearly all potential scenarios to evaluate the SIEM systems [15] comprehensively.

Cross-validation: These simulations were carried out on several datasets to ensure their solidity. This regarded the running of the simulations on different data segments

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and the testing of the output to verify viability [16].

Graphs

Table 1: DDoS Attack Mitigation Results

Metric	Traditional SIEM	AI-enhanced SIEM
Detection Time (seconds)	300	50
Mitigation Time (seconds)	600	100
Traffic Reduction (%)	50	90
Service Downtime (minutes)	30	5

Table 2: Phishing Attack Detection Results

Metric	Traditional SIEM	AI-enhanced SIEM
Detection Accuracy (%)	70	95
False Positive Rate (%)	10	2
False Negative Rate (%)	20	3
Average Response Time (seconds)	180	30

Table 3: Malware Intrusion Detection Results

Metric	Traditional SIEM	AI-enhanced SIEM
Detection Accuracy (%)	65	93
False Positive Rate (%)	15	5
False Negative Rate (%)	20	2
Time to Remediate (minutes)	60	15

Table 4: Scalability and Performance

Metric	Traditional SIEM	AI-enhanced SIEM
Max Events Per Second	1000	5000
CPU Utilization (%)	85	70
Memory Utilization (%)	80	65
Network Bandwidth (Gbps)	1	5

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Table 5: Resource Utilization and Efficiency

Metric	Traditional SIEM	AI-enhanced SIEM
CPU Utilization (%)	85	70
Memory Utilization (%)	80	65
Average Response Time (seconds)	180	30
Cost Efficiency (USD/hour)	10	7

Table 6: System Resilience and Robustness

Metric	Traditional SIEM	AI-enhanced SIEM
Time to Recover (minutes)	120.0	30.0
Detection of APTs (%)	60.0	95.0
Detection of Multi-vector Attacks (%)	55.0	90.0
System Uptime (%)	99.5	99.9

CHALLENGES AND SOLUTIONS

the Specific Difficulties Experienced in Practicing the Simulations and Their Deployment

The significant challenges that the delivery of secure and scalable SIEM systems supplemented by AI and ML in the cloud found were the following: These have had implications on different aspects such as integration, expandability, efficiency, security and acceptance among the target users.

Data Integration Challenges: Another challenge identified was the difficulty of incorporating multiple types of data into the SIEM system. Various data topologies, dissimilar data quality, and the massive amount of data produced by network devices, applications, and end-points present new challenges, making it extremely difficult to guarantee efficient data consumption and analysis [1]. Also, real-time data integration needed transport layers to process high volumes of data without any delays or loss of data in the series.

Scalability Issues: The sheer volume of security data that started to be generated became a key challenge, and the scalability of the SIEM systems became essential. Logical SIEM solutions were historically not as scalable, which resulted in the degeneration of the system's performance and escalated time to threat identification. The ability to gain elasticity to grow or decrease tomorrow's resources in proportion to demand in a cloud environment while protecting existing performance was challenging [2].

Performance Challenges: Another issue was keeping high performance, specifically the rate of detections and their reliability. While applying the proposed detection algorithms that incorporated AI and ML, an improvement in the detection abilities was observed, with an extra burden on computation processes. It was necessary to optimize their work and resource consumption to guarantee the general

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functionality of such algorithms and prevent them from causing a significant decline in system performance [3].

Security Concerns: The new challenges after implementing SIEM systems in the cloud include the following. Minimizing the risks of data leakage, ensuring data is secure from sieves like logistics, etc., and maintaining data that is intact and compliant with regulations were vital. Other issues identified in the cloud environment included data custodianship and security, which are multi-tenant-based [4].

User Adoption and Training: Thus, the migration to AI-supported SIEM tools entailed fundamental shifts in security teams' work. User adoption or acceptance in a similar manner was crucial, as was providing sufficient training to take full advantage of AI and ML-augmented features. The full potential of the improvements made to the SIEM systems was not achieved fully due to the resistance to change, especially learnt behaviours embraced in this context [5].

Solutions to the Challenges

The said challenges called for integrating several strategies that include technological solutions, best practices, and constant review.

Data Integration Solutions: To address the issues related to data integration, we have established solid and efficient data pipelines with the help of tools like Apache Kafka and Apache NiFi. These tools helped harmonize and integrate the data from multiple sources to create consistent, high-quality datasets. Moreover, it is convenient to mention that using the unified format for the data and utilizing the schema on the read concept provided opportunities to process the data efficiently [6].

Scalability Solutions: Building on the infrastructure scalability from cloud-based systems such as Amazon web service or Microsoft Azure, we implemented auto-scale to ensure resources could be proportionately adjusted depending on usage demand. Technologies like Docker and Kubernetes allowed for effective control of microservices and adjustments to the SIEM systems' horizontal scalability in case of increasing data [7]. Also, the parallel processing of AI and ML algorithms, besides their distribution across computing systems, improved scalability.

Performance Optimization: To achieve sustained high throughput, we integrated optimization strategies for AI & ML in our solution, namely model quantization and pruning. Amazon Web Services provided high-performance computing instances with GPU and TPU to increase computational performance, beginning from 8 [8]. Optimizing access, retrieval, and searching mechanisms led to faster access and response to questions asked about data.

Security Measures: To resolve security issues, we incorporated adequate data processing and communication measures and secured data storage procedures to enhance data security. Implementing IAM solutions also brought identity and access management, thereby allowing access control on data. Maintenance and consolidation of security procedures and policies were also conducted to meet the organization's regulatory conditions and the set international standards [9].

User Training and Adoption: We embarked on training programs and workshops for security teams to ensure user take-up. These included reorienting the users with the possibilities introduced by AI and ML, a showcase of use cases, and guided training. Also, integrating the user feedback ensured that the developed systems were user-oriented and aligned with the operations [10].

Lessons Learned

Simple lessons learned: it was rather valuable to implement AI-enhanced SIEM systems in the cloud environment, as it gave

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a clear understanding of how further activities in this area should be conducted.

Importance of Flexibility and Adaptability: Among the lessons, there were shining fragments, such as the necessity of using flexible and adaptable systems. Since cybersecurity threats are constant and are bound to change at some point, these SIEM systems must be able to adapt to change as well. It helped to stress modular architecture and microservices so one could update quickly and integrate new capabilities [11].

Continuous Monitoring and Improvement: This process had to be constant, and the improvements made to the SIEM systems installed had to be as frequent as the new threats that arose with time. The continuous performance check, model update, and system integration made it possible for the AI and ML to be ever-ready for future threats. Establishing feedback loops with Security teams promoted constant improvements in the feedback systems because of real-life experiences [12].

Collaboration and Knowledge Sharing: There was a need for good cooperation and communication between the data engineering team, the security experts to implement use cases and AI/ML experts. Integration enhanced coordination, meaning that professionals from various unknowns worked as a team, strengthening the thinking processes and thus providing the best solutions [13].

Balancing Automation and Human Oversight: As much as AI and ML helped improve the functions of SIEM systems, strengthening the automation over the human element was critical. Ensuring the staff performing security analysis of large applications could understand and validate the findings of the AI algorithms reduced the possibility of false positives and negatives [14]. Implementing relevant and efficient tools amplified the user's decision-making capabilities through interface designs and insight presentations. When analyzing the issues we faced during the simulations and implementation and using the acquired knowledge for designing the development plan, this project allowed us to implement a solid, protected, and efficient SIEM system improved with AI and ML tools. All these are noble towards promoting cybersecurity and ensuring organizations are safeguarded against emerging threats in the current complex world [15].

CONCLUSION

The current research focused on the advancements and the integration of secure and elastic SIEM systems, AI, and Machine Learning in a cloud platform. The main goals were to increase the effectiveness of managing, analyzing and responding to the enormous amounts of Security Information and Event Management systems data in real-time and to achieve a higher level of threat identification, as well as to provide further prospects for SIEM systems' development and their ability to perform constantly increasing volumes of work. The simulations included practical attacks like Distributed Denial of Service (DDoS) attacks, phishing attacks, malware attacks, and Advanced Persistent Threats (APTs). The results revealed enhanced threat detection productivity, accuracy, and AI and ML system capacity. These findings included threat detection, the company's ability to improve its scalability without compromising performance, efficient use of resources, existing stringent security measures, and the successful integration of users to the system through training. Greater use of optimization algorithms and proper utilization of cloud computing services contributed to such performance and effective encryption. Access control contributed to appropriate data security and compliance with regulations. Presumably, for these works' future, more advanced AI and ML models could be incorporated, the speed of data processing

in real-time could be increased, and the applications could be expanded to make them more user-friendly. The strengthening of cybersecurity talents could be supported by integrating SIEM systems with other security instruments and applying continuous learning processes for AI and ML. Also, expanding on the technical aspects of scalability and resource utilization, guaranteeing adherence to emerging standards, and creating unified defence strategies could improve global security. Therefore, it can be concluded that incorporating AI and ML into cloud SIEM systems has displayed a lot of potential in the context of cybersecurity. Thus, by considering the highlighted challenges and explaining further work based on the proposed concepts, organizations can improve SIEM systems' necessity, efficiency, and adaptability to additional threats in the sphere of cybersecurity.

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