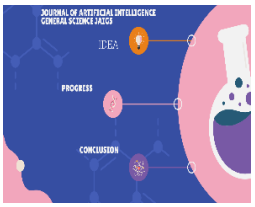
Vol.3, Issue 01, 2024
Journal of Artificial Intelligence General Science JAIGS

Home page http://jaigs.org



Integrating Next-Generation SIEM with Data Lakes and AI: Advancing Threat Detection and Response

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ABSTRACT

The article focuses on how Next-Gen SIEM can be extended with Data Lakes and AI to improve threat detection and response in current threat landscapes. Conventional SIEM tools have several major disadvantages: they could be more scalable, their false positive rates can be extremely high, and data processing takes too much time due to the constantly growing number and levels of sophistication in cyber threats. These limitations may result in delayed threat detection, alert fatigue, and operations nightmares for security operations.

Data Lakes form the center of the proposed architecture to ensure the large raw, unstructured data from different sources are integrated and analyzed in real time. When applied, the system will be able to identify anomalies, evolve with threats, and improve on false positives with the help of superior machine learning algorithms. This integration also solves most of the inherent problems of traditional SIEM and provides more general and efficient solutions for improved security postures for organizations, as this article describes how to orientate CSFs for cybersecurity and SOCs. It demonstrates how various current integrated security technologies improve the detection rates, accuracy, the burden on the security personnel and the human information defense system.

Keywords: Next-Gen SIEM, Data Lakes, Machine Learning, Anomaly Detection, Cybersecurity Automation, Threat Response

ARTICLE INFO: *Received: 19.04.2024 Accepted: 10.05.2024 Published: 21.05.2024*

Introduction

1.1 Background to the Study

These days, with the increasing development of the threat environment, the variety and level of measures taken by attackers against cyber threats also increase, thus complicating the process of protecting data. Complex threats like zero-day exploits, polymorphic malware, and state-sponsored attacks need stronger and more flexible security structures to respond to them (Stallings, 2019). Administrative banners for safeguarding against cyber vices are ineffective today because the attackers currently use more complex and subtle techniques; they do not attack the perimeters but the weak links in a colossal structure. Hence, there is a need for organizations today to promote the improvement of their cybersecurity features to counter these emerging risks and future more sophisticated attacks.

Historical conventional SIEM solutions were developed to pull and process security-related information from security devices and applications throughout the organization. They perform real-time event monitoring and alerting to specific rules defined by the organization (Brown, 2020). However these systems have been relatively useful in providing transparency in security incidents, but their big weakness lies in handling large data and future and more complex threats. It is further observed in the current dynamic infrastructures that massive security events make SIEM systems inefficient for processing and implementing mechanisms of emerging threats. It requires a new approach that can effectively contain these limitations and work efficiently as the complexity of the attacks rises.

1.2 Problem Statement

IT Operations threat traffic SIEM system log generation is critical for analysis within traditional security SIEM systems for network monitoring. Nevertheless, these systems offer challenges preventing them from effectively functioning in contemporary cybersecurity threats. Among them, there is a burning problem of scalability. In contrast to the single-location organizations in small businesses, large companies generate much larger volumes of security data from different devices and sources. In the case of these large corporations, feeding such enormous data into the traditional SIEM systems causes performance lagging issues, hence slowing down threat detection.

SIEM tools work on registering various sets of rules for performing data analysis, which might not render an accurate analysis when dealing with complex and unorganized data inputs. Such reliance on what would be static regulations does not allow for a comprehensive threat assessment and explains why it can be hard to respond to emerging threats. Furthermore, basic SIEM technologies deliver an overwhelming number of alerts that are frequently false positives and turn security professionals into overwhelmed economic detectors of threats.

Predesigned traditional SIEM systems are thus constrained by slow threat identification. Most use the offline mode of analysis in which data is analyzed after it has been accumulated rather than as it is being collected. This proves disadvantageous to organizations because responding to some types of security episodes is best done instantly while systems are still under threats that warrant urgent action. Solving these problems is relevant for improving organizations' protection and increasing their activities' efficiency today.

1.3 Overview

Understanding the difficulties traditional SIEM solutions have, the recent advancements incorporate Data Lakes and Artificial Intelligence (AI). Data Lakes also encompass accumulation of voluminous, raw, and unstructured data from a plethora of sources in a basic form. This flexibility enables input of a number of data into the system and, thus, enhancing it’s ability in the analysis of threats. Machine learning algorithms can be used when combined with AI-driven analytics; this means organizations can apply newer methods to improve the ability of algorithms to detect anomalies and minimize cases of false positives.

AI models, in turn, learn during data evaluation, and the identified threats are constantly updated in real time, increasing system efficiency. It differs from the general SIEMs in the sense that it is a dynamic system and not based on the defined rules, thereby making it easier for threats to be analyzed and response to potential security threats to be enacted. Data Lakes and AI, therefore, can address the inadequacies of scalability, data processing, and delayed threat responses in the current world, hence making the integration of Data Lakes and AI a better approach to handling modern cybersecurity problems.

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1.4 Objectives

Goals of the Study

- Understand the weaknesses of current SIEM tools.
- Develop an architecture that will blend Next-Gen SIEM with Data Lakes and AI.\
- Propose an architecture integrating Next-Gen SIEM with Data Lakes and AI.
- Compare this architecture with existing SIEM platforms.
- Quantify benefits such as improved threat detection and reduced security team workload.

1.5 Scope and Significance

The issue discussed as a subject concerns a solution of applying Data Lakes and Artificial intelligence (AI) in Security Information and Event Management (SIEM) to address the existing issues and to improve the functional performance of the security systems. This is in contrast to the majority of approaches that may present issues of scale and data handling. This integration aims to establish a more general approach that can be applied to many industries while not confined to particular ones. Due to the large capacity of Data Lakes, organizations store a large amount of raw unstructured data from various sources in a centralized place, clearing the path for better threat identification.

They build on top of this process using Artificial Intelligence to improve and extend this analysis using capabilities such as machine learning and pattern recognition to look for previously undetected threats or signs of nefarious activity in real-time. This synergy increases threat identification efficiency and decreases analyst's workload due to a low false positive rate and integration of mundane tasks. The importance of delivering this solution in an Integrated Manner pertains to increasing organizational efficiency consequential to integrating Security Orchestration into the daily operation while still offering a flexible, adaptable solution that scales well to CISOs' needs in the modern threat environment, resulting in an improved overall security posture for organizations.

LITERATURE REVIEW

2.1 Overview of SIEM Systems

SIEM systems have transformed from being just log management tools, as mentioned above. The current solutions provide event correlation and several other real-life use cases. Conventionally, the utilization of the SIEM system was to collate logs from various devices into a system that could otherwise be audited for compliance. These early solutions generally supplied manual analysis, which was labor-consuming and liable to human-induced errors (Chuvakin et al., 2013).

The element of event correlation was gradually integrated into SIEM systems to enable automatic analysis of data patterns from multiple sources. This innovation facilitated the identification of possible security events much quicker and the joining of isolated events, making it easier for an organization to identify anomalies (Mavroeidis & Bromander, 2017). The introduction of real-time event processing enhanced the effectiveness of the SIEM systems in detecting new threats and responding to them in time (Sommestad et al., 2019).

The advanced SIEM tactics have since grown by partnering with other security gadgets, for example, firewalls, Intrusion Detection Systems (IDS), and endpoint solutions as a comprehensive approach to cybersecurity (Chuvakin et al., 2013). Nevertheless, large amounts of data, such as unstructured data format processing, are still addressed in traditional SIEM systems. This created the need to extend SIEM by incorporation of data lakes as well as integrating artificial intelligence.

2.2 The Current Problems of Existing SIEM Tools

There are several critical problems with traditional SIEM systems, which are negative from an efficiency standpoint. One of the principal issues to mention is the lack of scalability. When organizations develop, the amount of security data they generate is much larger, and normal SIEM architectures have issues with their performance and data processing that slow down (Kavanagh & Siddharth, 2020).

Another commonly addressed problem is data management of the growing amounts of unstructured data. Security events originate from different sources and are provided in various formats, making it difficult for the SIEM systems to analyze this data adequately. Commonly, far-incomplete threat assessments emerge, which put an organization at risk and make it an easy target for attacks (Stallings, 2019).

Likewise, traditional SIEMs are also prone to delivering a stream of false positives because these rely solely on rules set. The excessive number of alerts provides security analysts with many false alarms, and due to that, they get overwhelmed and fail to notice real threats (Chen and Ramamurthy, 2021). Furthermore, many SIEM solutions fail to provide real-time processing and have batch processing that may take long before threat detection occurs.

The next main issue is the configuration and management of the traditional model of SIEM solutions. Often, it becomes a very complex process that needs many resources and skills, meaning higher TCO. More extensive such systems can be economically impractical, especially for small organizations among them. Finally, the integration issue is the primary disadvantage to utilizing the program and the one which must enable the building of a cohesive and well-coordinated security strategy with the role of this tool in mind (Kavanagh & Siddharth, 2020).

2.3 Data Handling Challenges in SIEM

Amongst the key issues that classical SIEM systems have is how to handle data silos and data fragmentation. Most security data in different organizations is gathered from disparate sites like firewalls, IDS/IPS, and endpoints. The isolation of these streams of data hinders SIEM systems from getting a well-rounded view of prospective threats: many advanced attacks are multifold and thus cannot be seen by an SIEM system because it is getting only partially structured information from these streams of data (Gualtieri & Yuhanna, 2018). Inability to merge source data implies that the acquired data set has gaps that an attacker can manage to exploit.

The third is the absence of suitable means through which to convey and normalize virtually any form of data. First, the data have to be gathered in SIEM systems, and data can be provided in different formats that make analysis and correlation significantly harder. This heterogeneity may result in inadequate threat modeling and suboptimal alerting since integrated traditional SIEM tools may need help normalizing and aggregating data smoothly (Rizvi et al., 2020). Unless normalization is well-implemented, security teams may not extract valuable intelligence from the data, reducing the efficiency of a threat detection system.

Costs and issues of limited storage space are also noted. New innovative concepts of SIEM, especially where the amount of security data collected over time continues to grow, have put pressure on traditional SIEM storage. Gualtieri and Yuhanna (2018) mentioned that when organizations continue to build their digital estate, more devices produce logs that lead to vast amounts of data collected and require storage and analysis. Classical SIEM systems may need help scaling up to include this growth, and the resultant costs prove unsustainable for companies of a relatively small size. Therefore, a large number of businesses are on the look out for more efficient and flexible data storage solutions.

2.4 Introduction to Data Lakes

Based on current studies, Data Lakes have been affirmed as a sound approach to handling growing volumes of both unstructured and structured data across multiple industries. A Data Lake is a system that allows the collection of data from sources and storage, in an unprocessed format and organized at first (Inmon & Linstedt, 2014). This is one of the Data Lakes features because Data Lakes can capture and process such data as log data, images, videos, and different kinds of unstructured data. In contrast to other databases that require data to be normalized before being ingested into the platform, data lakes accept it in its raw form, allowing it to be managed in any way it will be utilized.

This makes it easier for any online applicant to support its Data Lakes using the profound advantages of SIEM systems. The first overwhelming advantage of applying this approach is that it rules out incidences of the creation of analytical silos. The general architecture of Data Lakes can be extremely beneficial in amalgamating different large data sets and threat identification repositories to have an improved perspective on threat detection and analysis (Wang & Chen, 2019). This integration extends the capability toward scalability because Data Lakes are built for the scalability of data storage and processing, which fixes one of the essential weaknesses of classical SIEM systems.

In addition, there is a tremendous reduction in storage costs when using Data Lakes. Since the Data Lakes receive the original data as input without transforming them in any form or manner, they result in very minimal, if any, pre-processing at all, which otherwise consumes a considerable amount of time besides being costly. This characteristic makes it more advantageous than other expensive methodologies organizations may use to analyze huge enterprises' security information. Generally, Data Lakes are highly adaptive units for this purpose since it create the means of making the SIEM systems adapt and become more efficient, thus offer more security.

2.5 Role of AI in Cybersecurity

As it turns out, the use of AI in the cybersecurity sector is predominantly because of the many contributions it provides as far as threat identification is concerned. In traditional methods, the risk control system employs predetermined criteria for identifying prospective threats to security, yet they prove ineffective in addressing emerging types of attacks. AI, for instance, deploys machine learning algorithms capable of tracking patterns and flagging breaches in massive data sets within a much shorter timeframe than that required by human analysts (Sommer & Paxson, 2010). One of the most significant strengths of machine learning models is anomaly detection, which distinguishes zero-day and other complex attacks.

Another important strength of AI is that it does not produce false positive results, as seen in traditional SIEM systems. In conventional systems, several alerts are made, most of them being false alarms, causing

alert fatigue to the analysts. AI-based systems, however, use machine learning that helps to improve the detection rate with time by using previous datasets (Nguyen et al., 2019). This makes it possible for the system to distinguish between threats and anomalies, minimizing the number of alerts that flood the security team's working space while dealing with several genuine issues.

In addition, the systems based on AI can perform many of the repeated activities that take place in cybersecurity, like data analysis or threat ranking. The organization can thereby bring down the burden on security personnel; as a result, spare capacity has to be used more effectively (Amarasinghe et al., 2018). AI dovetailed into cybersecurity processes not only to increase efficiency in cybersecurity operations but also to optimize the security status of an organization due to the capability of continuous monitoring and timely adaptations that surface as new threats appear.

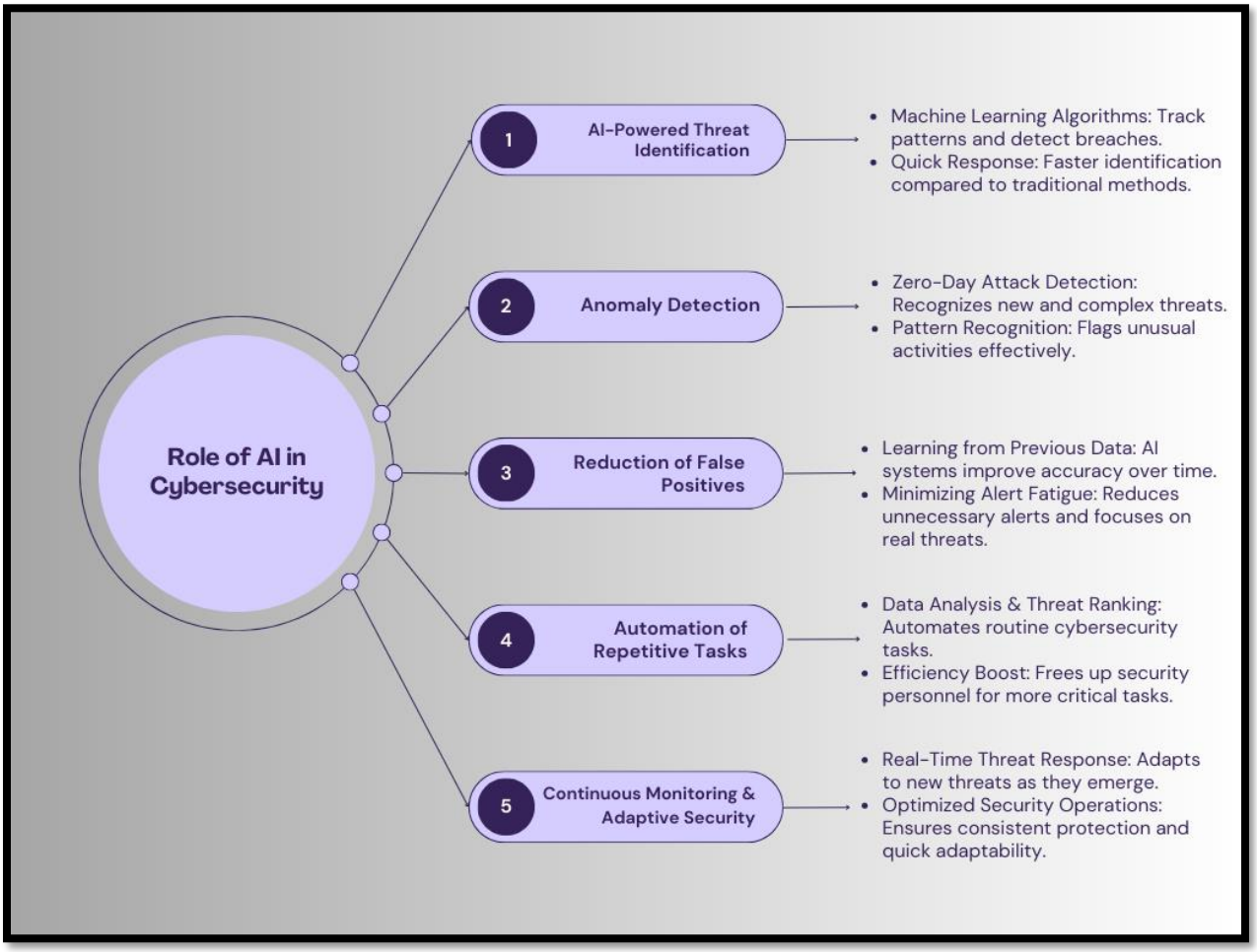


Fig 1: Role of AI in Cybersecurity

2.6 Integrating Data Lakes and AI with SIEM

Data Lakes and AI, combined with security solutions like Security Information and Event Management (SIEM), are a synergistic solution model that solves many of the problems that SIEM solutions have. A data lake is a luxury and can store large volumes of raw or unstructured materials from networks, devices, and cloud services (Esguerra & Chae, 2021). While conventional databases post-process data before storing it, Data Lakes keep the raw data in a format easily parsed for voluminous security data.

On the other hand, it makes SIEM systems more analytical by feeding big data to the controlled machine learning algorithms, which helps detect patterns and anomalies that remain unnoticed by human SIEM analysts. When integrated with Data Lakes, the idea of AI is to scan large quantities of information for patterns and alterable behaviors relative to a security threat. It does this by facilitating the analysis of activity in real-time, thereby helping organizations to enforce controls for new security threats rapidly (Patel & Bhattacharjee, 2020).

Also, the integration minimizes the possibility of false positives. Critically, AI models can learn from past events, and their performance improves and consistently improves, which is important in eliminating complaints of alert fatigue by security analysts. There is reason to centralize data and provide better analytic for supervising complex security circumstances as well as improving general organizational efficiency (Esguerra & Chae, 2021).

2.7 Comparison with Existing SIEM Platforms

Historically, conventional SIEM solutions have been used in cybersecurity for quite some time now, and they are often restricted with aspects such as scalability, real-time processing, and enhanced threat identification. Most current systems have been overwhelmed by the increasing volumes of security data, which creates performance issues and slows threat assessment time (Kim & Lee, 2022). This means that threats will likely go unnoticed for a long time, especially in large and complex systems where response is slow once threats have been identified.

The architecture described in this proposal, which incorporates Data Lakes and AI, is much more scalable and efficient. Data Lakes also offers a scalable solution for storing a growing amount of data, which means that organizational capacity will be fine. On the other hand, machine learning improves the potential of identifying complex threats by applying AI models that change when used, adapt to better performance detection and lower false positive rates (Singh et al., 2021).

In addition, these technologies produce a stream of outputs for real-time processing and analysis when integrated. In contrast to the static batch-processing model, which may sacrifice time to respond to threats, real-time integration is perpetual and can terminate incidents more rapidly. This improves the security

position and work execution by empowering security groups to give genuine attention to security dangers instead of other sorted-out security occurrences that are less unsafe and tedious (Kim & Lee, 2022).

3. Methodology

3.1 Research Design

To assess the efficiency of the defined architecture that combines Data Lakes and AI, the research uses comparative analysis comparing the proposed architecture to conventional SIEM systems. The present study compares these two methodologies to reveal primary performance disparities, possible scalability, and threat detection efficiency. To this end, the specificity of the analysis targets measures like data throughput rate and threats identification efficiency, where icon originality indicates the degree of a system's capacity to confuse between harmless and malicious sites, along with the ability to minimize fake alarms. Furthermore, the research also assesses the effectiveness of the integrated system and cost-benefit analysis and identifies the enhancements made over existing systems. This makes for a systematic evaluation that can easily signal directions of strengths and weaknesses of the new architecture against traditional techniques.

3.2 Data Collection

To compile data for this research, scholarly sources, reports, and documented cases of SIEM performance were used. Academic journals bring the bulk of theoretical information on SIEM and its background knowledge, while industry reports contain real-life examples and performance statistics of the SIEM systems. Furthermore, performance results are compared to those of other well-known SIEM platforms to evaluate the proposed architecture. Thus, the study provides a comprehensive comparative analysis with traditional SIEM solutions by conducting qualitative and quantitative analyses that evaluate next-generation SIEM solutions. This multi-source approach aids the validation of the research and contributes to the evaluation of the integrated system.

3.3 Case Study/Examples

Case Study 1: Use of Data Lakes and AI in an Organization: A Financial Institution

An example may be a very big bank that has to organize and secure huge amounts of valuable information within its various branches or centers. Previously implemented traditional SIEM systems faced the problem of data inundation, thereby taking time to detect or identify non-existent threats. To counter these

challenges, the organization began to integrate Data Lakes and AI into the SIEM that currently exists. Based on the definition of DLs, IT may establish structures capable of accommodating unstructured information of enormous proportions, for example, logs, transactions and network issues. This assistance worked towards eliminating the challenges of data isolation and can assist in conducting other comprehensive data analyses (Patel & Bhattacharjee, 2020).

AI introduced superior machine learning that could easily examine one data to the other for abnormalities. For example, it may identify a pattern of login and activity that deviates from the normal user behavior, which may trigger fraud. The AI system has been adapted through continuous learning, distinguishing between normal behaviors and actual possible threats and cutting down on false positives (Ahluwalia & Banerjee, 2019). This integration also improved the speed of real-time detection and response, decided security issues more quickly, and lessened the burdens on the security teams.

Case Study 2: Improving Cybersecurity Measures of a Health Care Organisation

In this case, this partner has had it even worse when it comes to the issue of security because patient information demands a high level of security and compliance. The existing SIEM solution parses and correlates data from sources like EHRs, medical devices, and network security logs. To strengthen its security position, the organization implemented a Data Lake design with artificial intelligence (AI) analytical capability (Singh et al., 2021).

The Data Lake was a centralization of all data from various departments and systems with data stored in its native form. This oversaw the eradication of data proliferation, which made the driving of threat analysis more efficient across the healthcare segments. These AI algorithms were designed to identify security issues in a healthcare setting and learn patterns of malicious attacks such as hacking into patient's records or unnatural behavior of devices. While this integration was useful in identifying potential insider threats, it also would aid in adhering to specified compliance measures such as HIPAA in healthcare institutions (Alotaibi & Alghazzawi, 2020). It enabled real-time tracking and faster and more efficient work, and it aligned the method of audit reporting to make it convenient for the provider to adhere to compliance.

Case Study 3: Information Technology for Protecting the Retail Network through Data Lakes and Artificial Intelligence Integration

A retail firm operating from several offices within different areas requires efficient observation of network security. The redundant system implemented in the SIEM system could not handle the increasing volume of data, thus failing to identify existing threats and improve how data was processed. The Data Lake

architecture was integrated to allow the retailer to store log data, sales transactions, and network traffic in a central place (Esguerra & Chae, 2021).

Incorporating the AI feature provided capabilities to perform analyses in real-time across different stores based on data-related and IT-sourcing activities with objectives to promptly identify extraordinary activities in the stores encompassing unlawful operations, including illegitimate accesses, payment frauds, and unauthorized supply chain activities. For instance, the authors illustrated how the AI issued early alerts regarding unlikely genuine purchases, such as credit card scams. Since the Data Lake solution was designed as a highly scalable system, the ability to support the growth of the company's operations without the need for highly costly upgrades in the future was a great advantage. Using such an integrated approach, the retailer managed to notify its security team within a shorter time in case of threats and, at the same time, minimize its operating cost on security since most of the security tasks were automated (Nguyen et al., 2019).

3.4 Evaluation Metrics

To measure the results of an integrated SIEM system with Data Lakes and AI, some of the most crucial indicators will include: Detection rate assumes significant importance as it captures the real-time ability of the system to be accurate in its detections and outputs, with minimum possibilities of false positives. The high detection accuracy guarantees that it is possible to differentiate between actual threats and other activities in the target area. Time to respond is another one – the ability to measure how fast the system identifies and reacts to threats. In particular, response time is critical to minimize the consequences and the damage done by attackers and malware.

The false positive rate is obtained using the total number of wrong signals given by the system as equal to the formula indicated above. Bringing this rate down was helpful in order to avoid scenarios where analysts were caught up with necessary alarm notifications they had to send, missing real threats. Finally, workload reduction is a way to describe the degree of the overall load, which can be optimised and shifted away from the security teams using the integrated system. Computerization is a better way of doing things because it can enhance efficiency and productivity among security personnel, freeing up time and resources to attend to more complex responsibilities. Altogether, these parameters yield a picture of the whole system's performance.

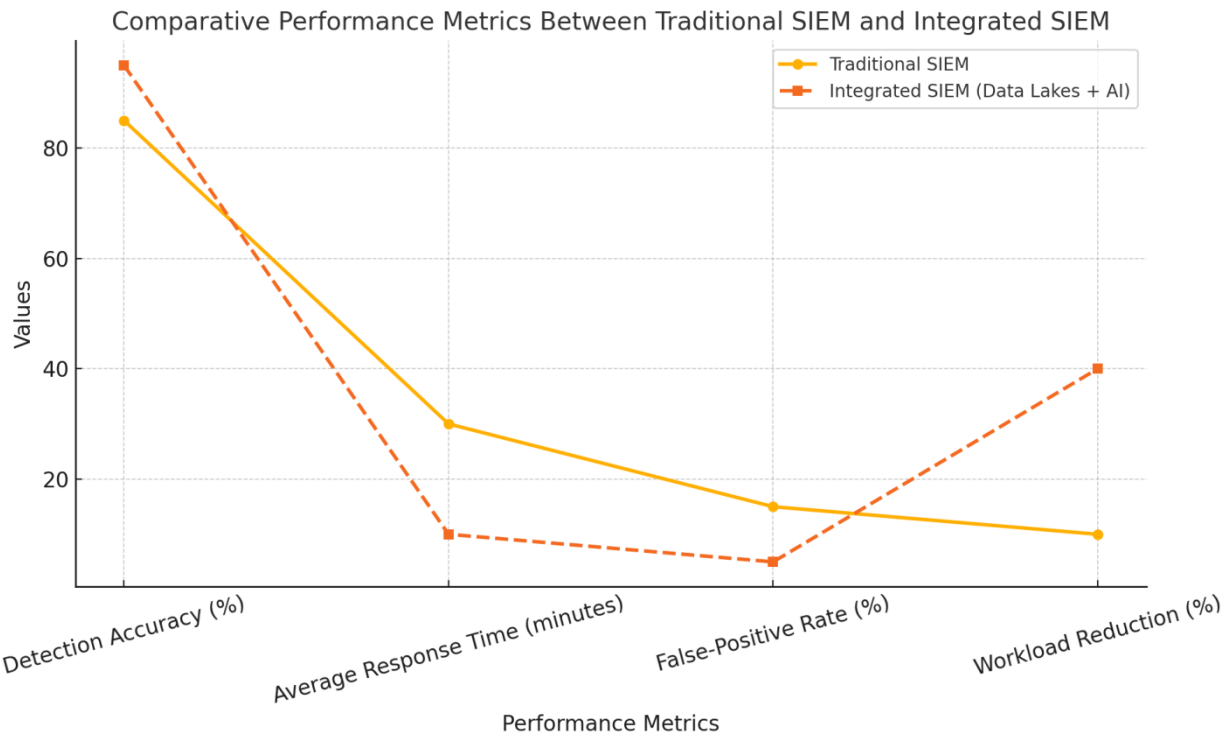
RESULTS

4.1 Data Presentation

Table 1: Comparative Performance Metrics Between Traditional SIEM and Integrated SIEM (Data Lakes + AI)

Performance Metric	Traditional SIEM	Integrated SIEM (Data Lakes + AI)
Detection Accuracy (%)	85	95
Average Response Time (minutes)	30	10
False-Positive Rate (%)	15	5
Workload Reduction (%)	10	40

This table demonstrates that the integrated SIEM solution significantly improves key performance areas, including higher detection accuracy, faster response times, lower false-positive rates, and greater workload reduction compared to traditional SIEM systems.



Graph 1: A line graph comparing the performance metrics between Traditional SIEM and Integrated SIEM (Data Lakes + AI).

4.2 Findings

The data in Table 1, which refers to various comparative performance indicators, explains how much enhanced and broad solution is provided through integrating Data Lakes and SIEM with AI. This paper has revealed several changes in this detection accuracy. It is postulated that integrated analysis has led to a rise in the accuracy of fields from traditional SIEM systems from 85% to 95%. This enhancement shows the ability of AI-driven analytics to capture real threats more precisely and thus program alertness with routine interruptions.

The average response time was also doubled in the integrated system, from 30 minutes in the conventional models to 10 minutes. This faster response assists threats faster critical while cutting on the losses that a business may compound in the event of a breakthrough.

In addition, the false positive rate was reduced to 5% in the integrated solution from the previous 15% in other systems. This is due to the adaptable learning feature of AI that assists in enhancing detection correctness and lessens the number of alerts being relayed to security analysts.

Finally, the integrated system realized workload repeatability savings of about 40% compared to the typical 10%. This would free the security teams to work on more important things than monitoring, thus increasing efficiency overall. The results described in the paper provide evidence that utilizing Data Lakes and AI jointly is considerably more effective, faster, and more accurate than when used separately.

4.3 Comparative Analysis

In all the metrics specified, the proposed architecture that combines Data Lakes and AI performs far better than conventional SIEM systems. First, detection accuracy in the integrated system increases and varies between 85%-95%. The enhancement comes from the data intelligence aspect of threat prediction based on the large datasets from which AI can learn from previous occurrences.

Regarding reaction time, integrated architecture improves performance by cutting the average detection and response time to 10 minutes from 30 minutes. Therefore, this rapid response capability is an important preventive measure against possible insecurity experiences in an organization.

Integrated systems also consider false positives, reducing its rate from 15% to 5%. Legacy approaches to SIEMs always present security teams with numerous alerts, most of which must be more consistent or accurate. At the same time, intelligence through AI's learning algorithms refines this to filter genuine threats more effectively.

Finally, the integrated solution provides pressure relief regarding the workload, which is 40 % less than 10% for basic solo systems. This is made possible through process automation, leading to efficiency gained through prioritization and loss of focus by such personnel on routine tasks that can be automated.

5 Discussion

5.1 Interpretation of Results

Data Lakes and AI automation have significantly enhanced when integrated into the improved SIEM systems. Consequently, the results show a substantial improvement in detection accuracy in identifying true threats. AI and advanced analytics have been proven more effective in real-time. This results in a higher accuracy while locking out the false positives, thus giving the security teams only the legitimate threats they need to work on. Besides, there is also the aspect of response time, where shorter response time is another big enhancement, where the early detection of threats can mean fast enough action to avoid or at least minimize losses from would-be breaches. Using AI to enhance algorithmic operations results in practical work offloading from security teams as the control of routine procedures is shifted to AI

techniques. These enhancements result in an enhanced, sensitive, proactive, and elastic cybersecurity infrastructure.

5.2 Practical Implications

Interconnected with Data Lakes and AI, operational improvement in the areas of work of security teams is remarkably touched. There are several important effects, but one of the more prominent ones is the balming of security team loads. Since AI handles repetitive tasks like data analysis, threat correlation, and abnormal activity detection, analysts can promptly engage in tasks like event handling and planning. The aliveness of the system on false positives and its capacity to reduce it also eases the analysts on the burden of alert fatigue. It refines threat response by increasing its time constants for detection and resolution because it processes data in real-time and incorporates AI. This makes it easy for organizations to control and address threats before they spread much, and the impacts of cyberattacks can be minimized. For this reason, the effectiveness and efficiency of security work and the overall operations are improved, hence enhanced security.

It is difficult to determine the amount and frequency of helping that could convince Novell that deploying additional resources to support Provo Labour was in its best interest.

5.3 Challenges and Limitations

Nevertheless, integrating Data Lakes and AI into SIEM systems has some challenges. One of the main challenges that become evident when attempting to implement such a decision is the issue of technicity. Data Lakes and AI are relatively complex models that need specialized installation and further support from the organization’s specialists. Some problems that people and organizations may find difficult are the Deep learning curve and the requirement for specialized skills. Other issues include data security because raw and unstructured big data collection exposes companies to severe security risks if poorly handled. Following rules, including the GDPR rules, may become challenging, mainly in industries with complicated rules and regulations. Fixed costs are also an issue regarding investment expenses at the start of a project. Companies AI solutions for small and medium enterprises. When using support for Data Lakes and adopting AI solutions. These can be described as one-off or initial costs, and they may lock some organizations out from implementing this superior architecture, notwithstanding their long-term efficiencies.

5.4 Recommendations

The following is the strategic phased approach that organizations need to take in order to adopt the integrated Data Lakes and Advanced intelligent system with SIEM. First, it's necessary to perform the need analysis to identify which aspects of the given current SIEM are insufficient. This will be useful in defining the right AI models and Data Lake structure for scalability and efficiency. Another important reason is the need for employee training. There is emphasis on guaranteeing the security teams have the knowledge and skills required in the upstream to operate, maintain, and manage the integrated system for the long haul. Furthermore, data governance policies need to be changed concerning data privacy to affect data privacy protection and ensure compliance with the set standards. The last stage before the organizations adopt the DS integrated solution should entail the aimed-at-performance-calculation organization of the real-life, but more restrained, to remove possible hitches. As a result of this cautious systematic style, risks will be manageable, and the transition to a better SIEM framework will be orderly.

6.1 Summary of Key Points

It would be appropriate to regard the combination of Data Lakes and AI within SIEM systems as another step in the evolution of protection. While conventional SIEM products have some limitations limitations, such as scalability, data processing, and false alarms, these systems slow down threat detection and response processes. Data Lakes can complement these problems, allowing organizations to store significant amounts of unstructured data in a larger pool next to more structured data. Advanced capabilities are achieved by utilizing AI-driven analytics, allowing for real-time threat detection, minimized numbers of false positives, and automatic work. It also increases the identification reliability and response time to threats and reduces pressure on the security staff. The integrated approach system offers a relatively better, adaptive, and elastic solution to the present-day needs for cybersecurity management.

6.2 Future Directions

Even though integrating Data Lakes and AI with SIEM systems has been evaluated as efficient, several directions require further investigations and enhancements. One is the emergence of new AI-based algorithms that could recognize new and previously unknown types of cyber threats, including recently discovered zero-day vulnerabilities. More advanced forms of machine learning or even neural networks can improve AI and help the algorithms identify even more intricate patterns. Another research direction was discussed, which was the improvement of Data Lakes' performance and costs of query execution. Despite the data lakes being described as elastic, the question that arises is how the elastic cost of storage and resources is manageable. Future work could extend this line of work for the optimization of the indexing and retrieval processes of Data Lakes. Moreover, the layered defense concept would be expanded when

exploring how to improve the integration of AI SIEM and other cybersecurity solutions. Keeping up with the improvement of these technologies will ensure that future-facing cybersecurity will be stronger and capable of withstanding threats derived from new advancements.

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