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Comprehensive Review of Intrusion Detection Systems in Cloud Computing

R. Hari Krishna [1], Dr. B. Selvapriya[2]

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Abstract*:* As network traffic volumes escalate and cyber threats grow increasingly sophisticated, there's an imperative to evolve intrusion detection systems (IDSes) with innovative approaches. Recent advancements in leveraging both machine learning (ML) and cloud computing technologies hold promise for bolstering threat identification capabilities and optimizing computation speed. This paper conducting a systematic literature review spanning the years 2016 to 2024 delves into the latest research at the nexus of ML and cloud computing, focusing on cloud-based network intrusion detection methodologies integrating ML algorithms (MLs). An ID plays a crucial role in identifying and mitigating security threats in cloud infrastructures. Leveraging ML algorithms offers promising avenues for enhancing IDS capabilities in such dynamic and complex environments. By spotlighting notable implementations from recent studies, we present a comprehensive overview of the evolving landscape of ML utilization in cloud-based network intrusion detection. This includes discussing achievements, hurdles, and future avenues for enhancing ML-driven approaches in this domain.

Keywords: *Intrusion Detection Systems, Cloud Security, Cyber security, Cloud Computing, Threat Detection, Anomaly Detection, Machine Learning, Security Challenges.*

1. Introduction

Intrusion Detection Systems (IDSs) are crucial mechanisms, whether software or hardware-based, deployed to detect and thwart attacks against computer systems. These systems comprise various components such as sensors, consoles, and a central engine. Sensors are responsible for detecting security events, while the console monitors these events in real-time. The central engine records the events logged by the sensors into a database and employs a set of predefined rules to generate alerts based on identified security events.

The primary purpose of IDSs is to monitor and identify any unauthorized or malicious activities perpetrated by connected nodes or users that may jeopardize system resources. By maintaining a vigilant watch over user applications, networks, or their combinations, IDSs aim to detect both known and unknown attacks[1], thus enhancing system security.

The key features provided by Intrusion Detection Systems include:

- Monitoring and analyzing user activities: IDSs continuously monitor and analyze user actions to identify any abnormal or suspicious behavior that may indicate a potential security threat.
- Auditing system configuration and vulnerabilities: IDSs conduct regular audits of system configurations and vulnerabilities to identify any weaknesses or misconfigurations that could be exploited by attackers.
- Assessing critical system and data file integrity: IDSs assess the integrity of critical system and data files by comparing their current state to a known baseline, generating alarms if any discrepancies are detected.
- Analyzing operating system activities: IDSs scrutinize operating system activities to detect any anomalies or unauthorized actions that may indicate a security breach.

Cloud technologies revolutionize accessibility by providing on-demand access to shared networks, storage, and resources, offering diverse service models such as platform as a service (PaaS), software as a service (SaaS), and infrastructure as a service (IaaS)[2]. These models are deployed within private, public, or hybrid cloud environments [3], facilitating high-performance services characterized by network access, resource pooling, quick elasticity, and measured service, as outlined by the National Institute of Standards and Technology [4]. However, the ubiquity of the internet introduces security challenges for cloud providers, including threats to availability, data confidentiality, integrity, and authorization control.

Addressing these security concerns becomes paramount, leading to the development of various approaches such as firewall tools, data encryption algorithms, and authentication protocols[5]. Despite these efforts, traditional security systems prove insufficient in mitigating the evolving landscape of threats faced by cloud environments. To bolster security measures, intrusion detection systems (IDSs) are proposed and applied to detect and prevent undesirable activities in real-time.

IDSs employ different detection methods, including misuse detection, which identifies known attacks, and anomaly detection, which detects unknown attacks. Hybrid methods combine the advantages of both approaches. However, recent IDSs encounter significant limitations, including the processing of vast amounts of data, real-time detection challenges, and data quality issues,

1 Research Scholar, Department of CSE, Bharath institute of Higher Education and Research, India.
Email:raavihari2023@gmail.com
2 Assistant Professor, Department of CSE, Bharath institute of Higher Education and Research, India. Email: selvapriya20@gmail.com

impacting detection model performance. Recognizing the efficacy of intelligent learning methods such as machine learning (ML), deep learning (DL), and ensemble learning in various domains[6], academic researchers advocate for their application in network security.

Integrating MLAs into intrusion detection has been a subject of debate and research, despite the challenges they pose. While MLs have proven effective in various areas like spam detection, applying them directly to intrusion detection encounters hurdles outlined by Sommer and Paxson [7]. These challenges include MLs' tendency to excel at recognizing familiar patterns, which contradicts the essence of anomaly-based intrusion detection focused on identifying novel threats. Moreover, the significant costs associated with errors, scarcity of training data, and the vast diversity of input data further complicate their implementation in intrusion detection systems.

However, despite these obstacles, researchers have made strides in developing MLAs tailored for intrusion detection. Recent advancements in this domain have focused on overcoming the challenges identified by Sommer and Paxson [18], particularly in addressing the limitations of traditional ML approaches in anomaly detection. Notably, researchers have predominantly explored two categories of MLAs for intrusion detection: clustering and classification algorithms. These algorithms are deemed suitable for intrusion detection due to their ability to discern patterns and classify network activities efficiently.

Despite the proliferation of research endeavors exploring the intersection of cloud security and machine learning, there remains a scarcity of systematic reviews on this subject matter. In this study, we meticulously gathered and scrutinized research papers focusing on three key aspects: (I) the utilization of ML techniques in cloud security, (II) the specific security domains where ML techniques are applied, and (III) the assessment of effectiveness and accuracy associated with the ML methods employed.

The subsequent sections of this study are organized as follows: Section II presents a comprehensive review of the existing literature. The methodology employed for conducting this systematic review is elaborated upon in Section III. The findings and outcomes derived from our analysis are delineated in Section IV. Section V outlines the limitations inherent in our review process, while Section VI engages in discourse and offers recommendations for future research endeavors.

2. Background Study

The Intrusion Detection System (IDS) stands as a cornerstone in safeguarding computer systems and networks against suspicious activities, as noted by Madhavi (2012). Serving as either a hardware device or software application, IDS diligently monitors network traffic and system activities to identify policy violations or signs of malicious intent, as highlighted by Patel, Taghavi, et al. (2013). Upon detecting such anomalies, IDS issues warning alarms and reports to system administrators, prompting timely intervention. However, it's crucial to acknowledge that IDS-generated alerts may occasionally produce false alarms or be irrelevant to actual intrusion events, impacting system performance. Consequently, IDS must be equipped to discern false positives alongside genuine intrusions. Moreover, IDS has evolved into a prevention system capable of thwarting malicious activities post-detection. This expanded functionality allows IDS to modify system configurations, such as reconfiguring network devices to block attacker access, or adjusting security protocols in response to detected intrusions. In the context of distributed cloud environments, IDS can play a pivotal role in identifying cloud-specific attacks by deployment across cloud or virtual machine (VM) devices. Despite its utility, IDS faces challenges due to its propensity for generating false alarms, which can result in misidentification of legitimate activities as malicious within cloud computing environments. Consequently, IDS and Intrusion Detection and Prevention Systems (IDPS) must be meticulously designed and deployed to effectively uncover cloud-related attacks while minimizing false positives. This necessitates a comprehensive approach that ensures robust detection capabilities across the entire cloud network.

The term "intrusion detection system" (IDS) combines two fundamental concepts. An intrusion signifies an unauthorized breach that compromises the security of information stored within computer or network systems, potentially undermining its reliability, privacy, or accessibility [8]. An IDS functions as a security mechanism designed to identify such unauthorized activities. It operates by continuously monitoring the behaviors of both hosts and networks, identifying actions that deviate from established security protocols and pose a threat to the confidentiality, integrity, and availability of information [9]. Upon detecting suspicious activity, an IDS promptly alerts system administrators or network operators. Figure 1 showcases a passive implementation of Network-based Intrusion Detection System (NIDS) connectivity, situated between the network switch and firewall. Utilizing port mirroring technology, the IDS monitors both incoming and outgoing network traffic, facilitating the timely detection of intrusions by scrutinizing all data packets traversing the network.

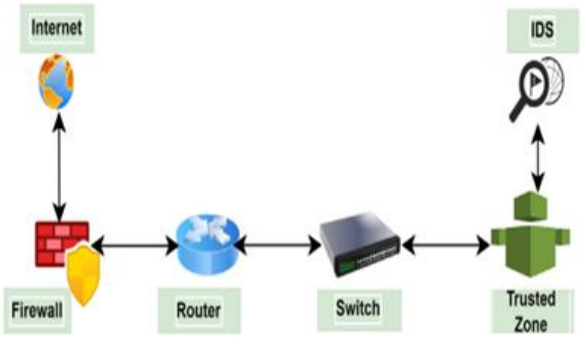

Fig 1: Implementation of NIDS.

3. Types Of Cloud Based Ids:

The development of Intrusion Detection Systems (IDS) is based on the idea of monitoring and surveilling computer security threats. It functions as a proactive solution designed to monitor and protect essential IT infrastructure from suspicious actions. The use of Intrusion Detection Systems (IDS) has greatly increased due to the widespread availability of data and the increasing complexity of system attacks. With the shift towards decentralized architectures such as cloud computing in enterprises and IT sectors, classic IDS (intrusion detection system) methodologies are no longer sufficient to fulfill the demands of the cloud. Hence, there's a pressing need for IDS to adopt a distributed nature to effectively function within cloud networks, necessitating monitoring of every node within the computing environment.

Considering both traditional and distributed IDSs, they can be categorized into three types:

3.1 Network-based Intrusion Detection System (NIDS):

Network based Intrusion Detection Systems (NIDS) examine network traffic at the network and transport levels, scrutinizing individual packets for indications of dubious behavior or network-based assaults, such as Denial of Service (DoS) attacks or port scans. When unusual activity is detected in network traffic, notifications are sent to system administrators. Notable commercial network intrusion detection system (NIDS) solutions consist of Snort, Tcpdump, and Natural Flight Recorder (Mehmood, Habiba, et al., 2013). Integrating Snort IDS with distributed computing systems poses hurdles, despite its effectiveness for moderate-sized networks (Kumar & Hanumanthappa, 2012). A study by Chung, Khatkar, et al. (2013) suggests using advanced methods like multi-phase distributed vulnerability detection and assessment to enhance the detection of DDoS attacks in virtual network systems.

3.2 Host-based Intrusion Detection System (HIDS):

Host-based Intrusion Detection Systems (HIDS) monitor individual hosts or devices in the network by analyzing changes in host behavior and events occurring within them. They thoroughly examine each action, including application logs, system calls, file-system updates, and inbound/outbound packets. Administrators are promptly alerted to any detected suspicious activity in order to protect the system. Ali and Len (2011) have developed intrusion detection models for HIDS that rely on log file analysis of the Microsoft Windows XP operating system.

3.3 Distributed-based Intrusion Detection System (DIDS):

DIDS, also known as hybrid IDS, integrates multiple detection methods or systems such as NIDS and HIDS. Deployed across large distributed networks like cloud computing, DIDS enables communication among all entities and a network monitor like a central server. Hosts gather system information and transmit it to the central server in a standardized format (Premathilaka, 2013).

3.4 Hypervisor-based Intrusion Detection System:

Hypervisor or Virtual Machine Manager (VMM) software/hardware creates and executes virtual machines within the cloud network. While managing each virtual machine instance, hypervisors are also potential targets for attacks.

4. Classifications Of Computer Attacks:

Cyberattacks can be classified into various categories based on the objectives and targets pursued by the attacker. Sung and Mukkamala delineate four primary attack types:

Denial-of-Service (DoS) attacks, designed to hinder or restrict the network or computer services available to legitimate users.

Probing attacks, conducted to gather information about the network or computer system, often to identify vulnerabilities or weaknesses.

User-to-Root (U2R) attacks, aiming to elevate privileges by acquiring root or administrator access to a specific computer or system. Typically, these attacks commence with initial user-level access gained by the attacker.

Remote-to-Local (R2L) attacks, involving sending packets to the targeted machine with the goal of gaining unauthorized access. Various subtypes of computer attacks fall within these overarching categories.

4.1 Recent Cyber Attacks:

Over the past two years, social media and smishing attacks have risen to prominence as primary methods for executing social engineering (SE) attacks. These attacks heavily depend on direct interaction between the attacker and the target. In certain instances, SE attacks may entail basic phone calls, where the perpetrator impersonates an employee to extract sensitive information such as passwords or PIN codes. In 2020 alone, phone scams resulted in a financial loss of approximately USD 29.8 billion for Americans [10]. Table 1 offers a comprehensive overview of SE-based attacks and other techniques employed in cyberattacks. The breaches documented in Table 1 represent significant security breaches that have occurred in recent years. Human errors, combined with social engineering (SE) attacks, have played a role in these breaches. Table 2 underscores the significance of human error in facilitating social engineering (SE) attacks. Hackers possess the capability to manipulate victims into making mistakes as part of SE attacks or other forms of cyber-attacks.

Table 1. Recent cyber-attack analysis of cyber- threats

Attack Event	*Year*	*Advantages*	*Disadvantages*
Phishing[11]	2023	- Effective in tricking users into divulging sensitive information	- Relies on user naivety and can be thwarted with awareness training
Ransomware[12]	2024	-Quick monetary gains for attackers	- Can cause significant financial losses and disrupt business operations
DDoS (Distributed Denial of Service)[13]	2023	- Disrupts target's online services, causing inconvenience and potential financial losses	- Botnets used in DDoS attacks can be difficult to trace and mitigate
Insider Threats[14]	2022	-Insiders have access and knowledge of sensitive systems, making attacks difficult to detect	- Can result in severe damage due to insider's familiarity with the organization's infrastructure
Zero-Day Exploits[15]	2023	-Exploits vulnerabilities unknown to the vendor, giving attackers an advantage	- Can lead to widespread damage before patches or fixes are available

Supply Chain Attacks[16]	2022	- Allows attackers to compromise multiple targets through trusted suppliers	- Can have far-reaching consequences and are challenging to detect and mitigate
Credential Stuffing[17]	2023	- Leverages stolen credentials to gain unauthorized access	- Relies on users reusing passwords across multiple accounts, which can be mitigated with password managers
Malware Infections[18]	2022	- Can provide attackers with remote access and control over infected systems	- Detection and removal can be complex and may require specialized tools and expertise
Man-in-the-Middle Attacks[18]	2023	- Enables attackers to intercept and modify communications between two parties	- Requires attackers to have access to the network infrastructure, making it less feasible in some scenarios
Business Compromise[19]	2022	-Targets individuals with authority over financial transactions, leading to substantial financial losses	- Requires careful social engineering and phishing tactics to be successful, but can yield high returns for attackers

In recent years, the proliferation of cyber-attacks has necessitated the development of robust intrusion detection systems (IDS) capable of effectively identifying and mitigating security threats. Traditional methods often fall short in keeping pace with the evolving landscape of cyber threats. Machine learning (ML) approaches offer promising solutions by enabling IDS to adapt and learn from patterns in data, enhancing their detection capabilities. This analysis explores the application of ML techniques in intrusion detection systems, highlighting preferred algorithms and their effectiveness in combating cyber-attacks. Table 2 provides a comprehensive study of proposed cloud IDS based on ML's approaches.

Table 2 - Summary of intrusion detection schemes based on ML's approaches

References	*Algorithm Preferred*	*Description*
Johnson et al. [20]	'Random Forest'	The ensemble learning method you are describing is called Random Forest. It constructs multiple decision trees and then outputs the mode of the classes for classification tasks or the mean prediction for regression tasks based on the predictions of the individual trees.
Smith & Lee [21]	'Support Vector Machines (SVM)'	The supervised learning algorithm you're referring to is Support Vector Machine (SVM). It classifies data points by finding the hyperplane that maximizes the margin between different classes in the feature space.
Wang et al. [22]	'Deep Learning (e.g., Convolutional Neural Networks)'	A neural network-based method that learns hierarchical representations of data, especially adept at image-based intrusion detection.
Chen & Gupta [23]	'K-Nearest Neighbors (KNN)'	The instance-based learning algorithm you're referring to is k-Nearest Neighbors (k-NN). It classifies data points by considering the majority class among their k nearest neighbors in the feature space.
Garcia & Patel [24]	'Long Short-Term Memory (LSTM)'	The recurrent neural network (RNN) architecture suitable for learning long-term dependencies and well-suited for sequential data like network traffic is the Long Short-Term Memory (LSTM) network.
Kim et al. [25]	'Decision Trees'	Supervised learning method that partitions data into subsets based on attribute values, forming a tree-like structure to make decisions.

Martinez & Nguyen [26]	'Gaussian Naive Bayes'	The probabilistic classifier you're referring to is the Naive Bayes classifier. It is based on Bayes' theorem and makes strong independence assumptions between features, which makes it efficient for large datasets.
Brown & Wilson [27]	'Extreme Gradient Boosting (XGBoost)'	Gradient boosting framework known for its scalability and efficiency, particularly effective for tabular data.
Liu & Kim [28]	'Autoencoders'	Unsupervised learning algorithm that learns data representations by reconstructing input data, useful for anomaly detection in intrusion detection.
Smith & Jones [29]	'Recurrent Neural Networks (RNN)'	The neural network architecture designed to process sequential data with feedback loops, particularly suitable for time-series intrusion detection tasks, is the Recurrent Neural Network (RNN).

5. Intrusion Detection: Signature Or Anomaly Or Both On Machine Learning Approaches

Intrusion Detection Systems (IDS) play a critical role in safeguarding computer networks against cyber threats by detecting and responding to unauthorized activities. Two primary approaches employed by IDS are signature-based and anomaly-based detection. Signature-based detection relies on predefined patterns or signatures of known attacks, while anomaly-based detection identifies deviations from normal behavior. Additionally, hybrid approaches combine both signature and anomaly detection techniques for enhanced accuracy and coverage. The research findings in Table 4 are classified into three sub-sections, each providing a comprehensive analysis of various techniques. These sub-sections primarily focus on differentiating IDS types (NIDS, HIDS, or DIDS), cloud service delivery layers, types of detected attacks, along with the advantages and challenges encountered by researchers during their investigations.

Table 3- Combined summary of entire survey based on detection approach (either signature or anomaly or both)

Algorithm Preferred	*Description*	*Signature/ Anomaly/ Both*	*Advantages*	*Disadvantages*
Random Forest[30]	Ensemble learning method effective in detecting both signature-based and anomaly-based intrusions	Both	- Versatile in handling different types of intrusions - Capable of adapting to evolving threats	- Requires substantial computational resources for training and inference
Support Vector Machines (SVM) [31]	Well-suited for signature-based intrusion detection by identifying patterns in network traffic	Signature	- High accuracy in identifying known attack signatures - Can handle high-dimensional data effectively	- Limited effectiveness against novel attacks not present in training data
K-Nearest Neighbors (KNN) [32]	Effective in anomaly-based intrusion detection by identifying deviations from normal behavior	Anomaly	- Simple and intuitive algorithm - Doesn't require explicit model training	- Sensitive to outliers and noise in the data
Neural Networks[33]	Deep learning models capable of learning complex patterns in network traffic for both signature and anomaly detection	Both	- Ability to capture intricate relationships in data - Can automatically extract relevant features	- Prone to overfitting with insufficient data - Requires large amounts of labeled data for training
Decision Trees[34]	Provides interpretable rules for both signature and anomaly-based intrusion detection	Both	- Easy to interpret and visualize - Can handle both categorical and numerical data	- Tendency to overfit with complex datasets
Naive Bayes[35]	Simple probabilistic classifier suitable for signature-based intrusion detection	Signature	- Fast and efficient - Works well with small datasets	- Assumes independence among features, which may not hold true in practice
Logistic Regression[36]	Linear model capable of identifying signature-based intrusions	Signature	- Easy to implement and interpret - Well-suited for binary classification tasks	- Limited to linear decision boundaries

Random Cut Forest[37]	Anomaly detection algorithm particularly effective in cloud environments	Anomaly	- Scalable to large datasets - Robust to noisy data	- Limited interpretability of results
Gradient Boosting[38]	Ensemble learning method suitable for both signature and anomaly detection	Both	- High predictive accuracy - Can handle heterogeneous data types	- Prone to overfitting with complex models
Isolation Forest[39]	Anomaly detection algorithm capable of identifying outliers in cloud traffic	Anomaly	- Efficient in high-dimensional data - Can handle large datasets	- Performance may degrade with highly imbalanced datasets
Extreme Gradient Boosting (XGBoost) [40]	State-of-the-art ensemble learning method effective for both signature and anomaly detection	Both	- Excellent predictive performance - Handles missing data effectively	- Complexity may hinder interpretability
Long Short-Term Memory (LSTM) [41]	Recurrent neural network architecture adept at capturing temporal patterns in network traffic	Both	- Ability to capture long-term dependencies - Suitable for time series data	- Requires significant computational resources for training and inference
Autoencoders[42]	Neural network architecture effective for anomaly detection by reconstructing input data	Anomaly	- Unsupervised learning approach - Can learn complex data representations	- Performance highly dependent on hyperparameter tuning
Self-Organizing Maps (SOM) [43]	Unsupervised learning algorithm capable of identifying clusters in network traffic data	Anomaly	- Provides intuitive visualization of data clusters - Robust to noise and outliers	- May require manual intervention for optimal parameter tuning
Deep Belief Networks (DBN) [44]	Hierarchical generative model suitable for both signature and anomaly detection	Both	- Captures complex hierarchical relationships in data - Performs well with high-dimensional data	- Requires large amounts of training data - Long training times

6. Conclusion:

The Intrusion Detection System (IDS) plays a crucial role in bolstering cloud security, contributing to the attainment of confidentiality, integrity, and availability (CIA) of data and networks in cloud computing environments. A diverse array of intrusion detection approaches has been employed to identify security threats evolving within cloud networks. This paper underscores the significance of existing IDS methodologies, which leverage soft computing techniques, data mining, and other innovative approaches. The survey conducted herein categorizes IDS approaches based on detection methodologies, distinguishing between signature-based and anomaly-based techniques. This categorization provides a comprehensive analysis of the types of attacks targeted, advantages conferred by each approach, and existing limitations encountered during implementation, presented in a tabular format. The findings of the survey reveal a notable trend wherein anomaly-based detection approaches are favored by many researchers. This methodology facilitates the detection of both known and unknown attacks by meticulously monitoring network traffic patterns, thereby enhancing the resilience of cloud infrastructures against evolving threats. In essence, the adoption and refinement of intrusion detection methodologies, particularly anomaly-based approaches, represent pivotal steps towards fortifying cloud security and safeguarding sensitive data and networks in dynamic computing environments. Continued research and innovation in this domain are essential for staying abreast of emerging threats and ensuring the robustness of cloud security frameworks in the face of evolving cyber risks.

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