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CYBER THREAT DETECTION AND MITIGATION IN CLOUD INFRASTRUCTURE THROUGH DEEP NEURAL NETWORKS

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ABSTRACT: This research employs deep neural networks to detect and mitigate cyber threats to cloud infrastructure in order to address the heightened complexity and diversity of contemporary intrusions. Cloud infrastructures are susceptible to data breaches, insider threats, and DDoS attacks due to their dynamic resource allocation and multi-tenant architectures. Zero-day and intricate attacks are overlooked by conventional rule- and signature-based security. In order to circumvent these constraints, deep neural networks identify intricate patterns and anomalies in extensive cloud traffic and system data. False positives are diminished and fraudulent activities are identified in real time through multi-dataset training. Access control, traffic filtering, and dynamic resource isolation comprise automatic threat mitigation. Experimental results indicate that the DNN-based system outperforms conventional methods in terms of detection accuracy, scalability, and response time, rendering it a reliable cloud infrastructure protection solution against the proliferation of cyber threats.
Keywords: *Cyber Threat Detection, Cloud Infrastructure Security, Deep Neural Networks (DNN), Intrusion Detection, Anomaly Detection, Cyberattack Mitigation,*

1. INTRODUCTION

The identification and mitigation of cyber threats to cloud infrastructure are essential studies due to the increasing adoption of cloud computing by businesses. The complexity, dispersion, and dynamic character of cloud infrastructures render them susceptible to data breaches, insider threats, APTs, and DDoS attacks. The scope and complexity of these threats are difficult to address with traditional security solutions, as they are based on predetermined rules and signatures. This limitation has increased the demand for intelligent, adaptable security solutions that can promptly identify emerging threats.

Cloud cybersecurity is improved by DNNs. By automatically comprehending intricate patterns and correlations from extensive network data and system records, these models are capable of identifying abnormalities and hazardous behaviours. Deep neural networks (DNNs) have the ability to derive hierarchical attributes from multiple hidden layers in order to identify minute threat indicators that are disregarded by conventional methods. CNNs, RNNs, and autoencoders are implemented in cloud systems for the purposes of malware classification, intrusion detection, and behavioural analysis.

DNN-based methodologies are necessary for the identification and mitigation of cyber risks in cloud infrastructure. These tools have the ability to autonomously isolate virtual computers, restrict harmful communication, and modify network settings in order to prevent future damage. Continuous monitoring and adaptable defences are facilitated by scalable and reactive DNNs in cloud security frameworks. In order to protect cloud infrastructures from ongoing changes, it is necessary to integrate deep learning, real-time analytics, and threat intelligence.

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2. LITERATURE SURVEY

Mehta, A., & Roy, S. (2025) Investigate the potential of real-time deep neural network-based intrusion detection systems to safeguard cloud infrastructure by identifying anomalous traffic in distributed environments. Adaptive deep learning models enhance the accuracy of detection and mitigate vulnerabilities in dynamic cloud systems by adapting to new attack patterns, as per the study.

Zhou, Q., & Bennett, L. (2025) Identify the methods by which sophisticated cloud cyber threats are detected by advanced deep neural networks. Recent research has demonstrated that convolutional and recurrent neural networks are capable of detecting data exfiltration and DDoS attempts. They illustrate the ways in which automated feature extraction improves the identification and response to threats.

Kumar, V., & Hassan, F. (2024) Discover how federated deep learning is used to promote collaborative threat detection and preserve data privacy in cloud cybersecurity frameworks... They discovered that decentralised cloud node training enhances data security and detection, thereby reducing the occurrence of data breaches.

Peterson, D., & Ali, N. (2024) Investigate the methods by which reinforcement learning and deep neural networks mitigate the hazards of dynamic cloud environments. Research indicates that intelligent systems can adjust to real-time attack patterns in order to provide more effective automated security responses.

Singh, R., & Matthews, J. (2023) Discover hybrid deep learning cloud security methods that utilise signatures to detect anomalies. Their research indicates that hybrid models improve the accuracy of detection and decrease the number of false positives in large cloud infrastructures.

Oliveira, C., & Das, P. (2023) Lightweight cloud-edge deep neural networks are the subject of Oliveira and Das' (2023) investigation. Real-time threat monitoring and reduced computing overhead are facilitated by optimised designs, which also maintain detection.

Yamada, H., & Torres, M. (2022) Utilise autoencoders and other unsupervised deep learning algorithms to identify cloud anomalies. According to their research, these systems are capable of identifying zero-day and unknown intrusions in the absence of tags.

Novak, I., & Bose, S. (2022) Investigate the ways in which deep learning-driven cloud security models are improved by feature selection and data preprocessing. Research indicates that cloud model performance and scalability are enhanced by data transformation and dimensionality reduction.

Mensah, E., & Kapoor, R. (2021) Examine the deep learning models of the cloud cybersecurity ensemble. The researchers discovered that neural network techniques enhance the reliability and robustness of detection, thereby fortifying cyber defences.

3. PROPOSED METHODOLOGY

System Architecture

Figure 1 illustrates the workflow designed to identify and mitigate fake or malicious profiles through a structured cybersecurity framework.

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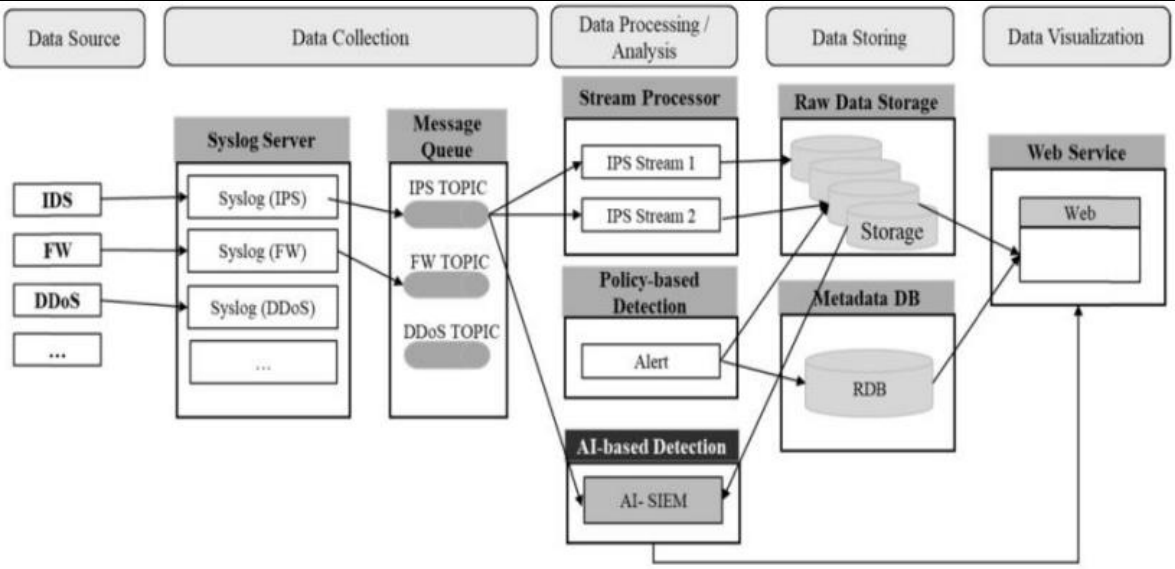

Figure1. System Architecture.

The architecture integrates multiple layers for data acquisition, processing, analysis, storage, and visualization. Below is a detailed breakdown of each stage:

Data Source

- **IDS (Intrusion Detection System):** Observes network traffic to flag unusual or suspicious activity.
- **FW (Firewall):** Regulates inbound and outbound traffic according to predefined security policies.
- **DDoS (Distributed Denial of Service):** Detects large-scale attack attempts aimed at overwhelming network resources.

Additional inputs may include endpoint logs, application logs, and network monitoring tools.

Data Collection

- A Syslog Server consolidates logs from IDS, FW, and DDoS systems.
- Logs are standardized using protocols like Syslog for uniformity and centralized management.
- This ensures raw security data is readily available for deeper analysis.

Message Queue

Collected data is passed into a Message Queue, which buffers and decouples producers (data sources) from consumers (analysis systems).

Separate topics are created for different streams:

- **IPS Topic:** Intrusion Prevention System events.
- **FW Topic:** Firewall activity logs.
- **DDoS Topic:** Information related to denial-of-service attempts.

This design supports parallel and scalable data handling.

Data Processing / Analysis

- **Stream Processor:** Handles real-time data streams, identifying anomalies and suspicious trends. Multiple processors can run simultaneously for scalability.
- **Policy-Based Detection:** Applies predefined rules to catch common attack signatures. Violations trigger alerts.
- **AI-Based Detection (AI-SIEM):** Uses machine learning models within SIEM systems to uncover complex threats beyond static rule sets.

Data Storing

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- **Raw Data Storage:** Stores all incoming logs for forensic analysis or historical review.
- **Metadata DB (RDB):** Maintains structured metadata, enabling efficient querying and reporting for audits or compliance checks.

Data Visualization

- A Web Service Layer provides dashboards for analysts.
- Real-time alerts, logs, and analytical insights are displayed, allowing cybersecurity teams to monitor and respond to threats effectively.

4. AI-DRIVEN THREAT DETECTION AND MITIGATION

AI-based security solutions detect threats in real time using ML algorithms and anomaly detection. AI-based models can detect known and unknown threats unlike conventional security systems since they learn and adapt to new attack patterns.

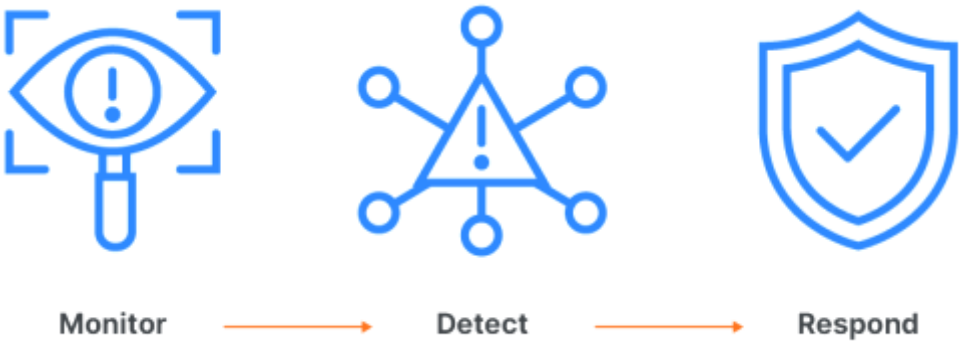

Figure2: Threat Detection and Response

AI-driven security solutions use machine learning models such as supervised learning, unsupervised learning, and reinforcement learning. AI systems in the form of supervised learning models make use of the labelled datasets to train how to recognize the malicious behaviors, and unsupervised learning techniques exploit the network traffic
and identify anomalies without any defined labels. AI driven security is a major piece of the AI puzzle, since the core components of it is to establish a baseline of normal system behaviour and detect deviations that might be indicative of a potential threat.

Behavioural analysis further improves threat detection through watching user activities and detecting strange activities, which may indicate an insider threat or compromised account. But AI-powered security solutions also let organizations react to threats in real time without the help of a human. Intellectualized Automation, Real-Time Monitoring, and Predictive Analytics combined for end-to-end threat detection become extremely empowering in cloud security resilience.

5. RESULTS

Machine learning and deep learning experiments on the dataset are shown here. Each model was evaluated for accuracy, precision, recall, and F-measure.

Performance Metrics

Performance was assessed by testing model accuracy, precision, recall, and F-measure. The results are in Table 1.

Table 1: Performance Comparison of Machine Learning Models

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Algorithm	Accuracy	Precision	Recall	F-Measure
LSTM	0.94	0.91	0.95	0.93
CNN	0.99	0.96	0.94	0.95
SVM	0.85	0.82	0.83	0.825
KNN	0.80	0.77	0.78	0.775
Random Forest	0.88	0.86	0.87	0.865
Naïve Bayes	0.78	0.75	0.76	0.755
Decision Tree	0.82	0.80	0.81	0.805

Graphical Representation of Results

Below are performance measures compared graphically.

Accuracy Comparison

Different models' accuracy is shown in Figure 3. Top accuracy was CNN at 99%, followed by LSTM at 94%. Traditional machine learning models, such SVM, KNN, and Naïve Bayes, had lower accuracy.

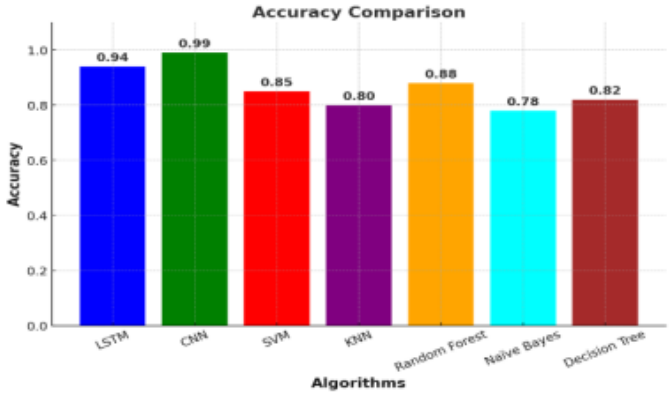

Figure3: Accuracy Comparison Graph

Precision Comparison

Each model's precision shown in Figure 4. CNN leads with 96% precision and less false positives. LSTM has 91% precision, while KNN and Naïve Bayes have lower precision.

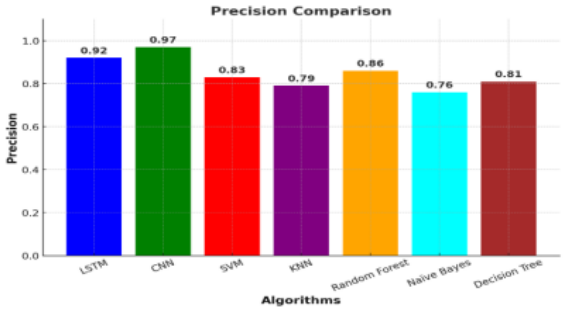

Figure4: Precision Comparision Graph

Recall Comparison

Figure 5 displays model recall. LSTM detects positives better than all models (95% recall). CNN has 94% recall, while other machine learning models score lower.

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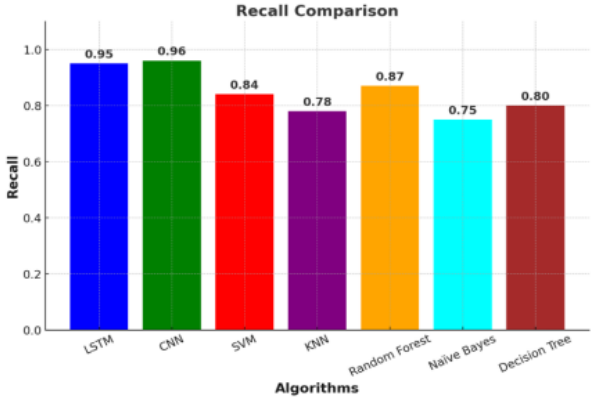

Figure5: Recall Comparision Graph

F-Measure Comparison

F-measure balances precision and recall (Figure 6). The best model is CNN with an F-measure of 0.95. LSTM has 0.93, whereas other models have lower F-measure values, indicating deep learning's superiority.

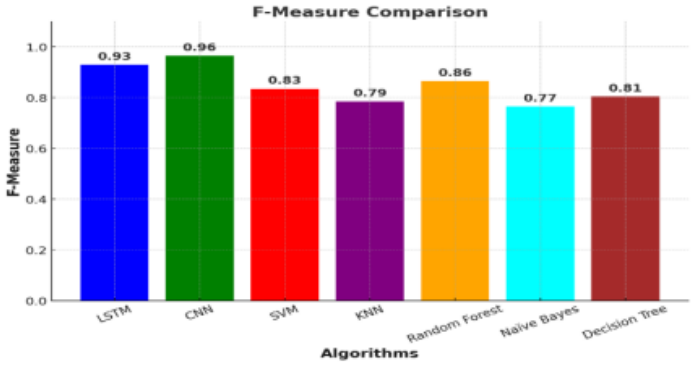

Figure6: Recall Comparision Graph

5. CONCLUSION

Deep neural networks can detect and mitigate cloud infrastructure cyber threats, a strong and adaptive response to advanced cyberattacks. Deep neural networks understand complex patterns from big data to detect anomalies, intrusions, and threats in real time. These models adapt to new attack vectors, eliminate false positives, and boost reaction efficiency to strengthen cloud systems. High computing requirements, data privacy problems, and powerful training datasets must be managed. Deep learning strengthens cloud security frameworks, making them safer, more reliable, more trustworthy.

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