Cloud Data Centre Security Using RNN, CNN, and LSTM for Anomaly and Intruder Detection: A Review

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Abstract. Cloud data centres are critical infrastructures that store and process massive volumes of sensitive data. With the rapid growth of cloud computing, security threats such as intrusions, Distributed Denial of Service (DDoS) attacks, malware injection, and insider attacks have significantly increased. Traditional rule-based intrusion detection systems (IDS) struggle to detect sophisticated and zero-day attacks. Deep learning techniques such as Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks have emerged as powerful tools for anomaly and intruder detection. This paper reviews recent advancements in deep learning-based security mechanisms for cloud data centres. It analyzes architectures, datasets, performance metrics, advantages, limitations, and future research directions.

Keywords: Cloud Security, Data Centre Security, RNN, CNN, LSTM, Intrusion Detection System, Anomaly Detection, Deep Learning.

I.INTRODUCTION

Cloud computing has transformed modern IT infrastructure by enabling scalable, on-demand services. Major cloud service providers like Amazon Web Services, Microsoft Azure, and Google Cloud Platform manage large-scale data centres that host enterprise and personal data.

However, cloud environments face various security challenges:

Multi-tenancy vulnerabilities

Virtual machine (VM) escape attacks

Network-based intrusions

Insider threats

Advanced Persistent Threats (APT)

Traditional signature-based IDS cannot effectively detect unknown or evolving threats. Therefore, machine learning and deep learning approaches are increasingly adopted for intelligent anomaly detection.

II.Background and Related work

2.1 Intrusion Detection Systems (IDS) have evolved significantly over the past decade in response to increasing security threats in cloud data centres. Traditional signature-based systems were initially deployed to detect known attacks; however, the dynamic and distributed nature of cloud environments necessitated more intelligent and adaptive detection mechanisms. With the emergence of deep learning, models such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) have demonstrated superior performance in anomaly and intrusion detection tasks. This section presents a comprehensive year-wise review of these techniques along with reported efficiencies.

A. Early Deep Learning Adoption in IDS (2015–2016)

The integration of deep learning into intrusion detection began gaining attention around 2015. Tang et al. [1] applied Deep Neural Networks (DNN) to the NSL-KDD dataset and demonstrated that deep architectures significantly outperform traditional machine learning algorithms such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN). Their approach achieved a detection accuracy of approximately 97.5%, establishing deep learning as a promising solution for cloud-based IDS.

In 2016, Kim et al. [2] proposed a CNN-based intrusion detection framework capable of automatically extracting hierarchical features from raw network traffic data. Unlike traditional methods requiring manual feature engineering, CNN-based IDS systems learn discriminative patterns directly from input data. Their model achieved 98% detection accuracy, with a noticeable reduction in false positive rates compared to shallow learning approaches.

These early studies highlighted the potential of deep architectures in handling high-dimensional cloud traffic data while improving detection efficiency.

B. RNN-Based Sequential Intrusion Detection (2017)

As cloud traffic inherently exhibits temporal characteristics, researchers began exploring recurrent architectures. Yin et al. [3] introduced a Recurrent Neural Network (RNN)-based IDS model to capture sequential dependencies in network flows. The model was evaluated on benchmark datasets and demonstrated improved performance in detecting time-dependent attacks such as brute force and probing attempts.

However, due to the vanishing gradient problem, standard RNNs struggled with long-term dependency learning. The reported accuracy ranged between 83% and 86%, which, although competitive, was lower than CNN-based models. Nevertheless, this work laid the foundation for advanced recurrent models tailored for cloud intrusion detection.

C. LSTM-Based Intrusion Detection (2018–2020)

To address the limitations of traditional RNNs, Long Short-Term Memory (LSTM) networks were introduced into IDS research. LSTM models incorporate memory cells and gating mechanisms to preserve long-term dependencies in sequential data.

In 2018, Alrawashdeh and Purdy [4] proposed an LSTM-based IDS for cloud environments. Their model effectively detected DDoS attacks and other network anomalies with an accuracy of 98.8%. The study demonstrated that LSTM networks significantly improve detection of slow-rate and multi-stage attacks.

Building upon this work, Kim et al. [5] introduced a hybrid CNN-LSTM architecture in 2019. The CNN component performed automatic feature extraction, while the LSTM captured temporal dependencies. Evaluated on the CICIDS2017 dataset, the hybrid model achieved 99.2% accuracy, outperforming standalone CNN and LSTM models.

In 2020, Vinayakumar et al. [6] proposed a stacked LSTM architecture designed for large-scale cloud traffic analysis. The deep stacked configuration improved anomaly classification and scalability, achieving 99.5% detection accuracy on the UNSW-NB15 dataset. This study confirmed that deeper recurrent models can effectively handle high-volume cloud data centre traffic.

D. Advanced and Distributed Deep Learning IDS (2021–2024)

With the expansion of distributed cloud infrastructures, researchers began focusing on privacy-preserving and scalable IDS solutions. In 2021, Otoum et al. [7] proposed a federated learning-based LSTM IDS for distributed cloud environments. This approach enabled collaborative model training without sharing raw data among cloud nodes. The system achieved 97–99% accuracy, demonstrating both security and privacy benefits.

In 2022, Ferrag et al. [8] integrated Explainable Artificial Intelligence (XAI) techniques with CNN-LSTM architectures to enhance transparency in intrusion detection decisions. Their approach achieved approximately 99% detection rate while providing interpretability for security analysts.

Recent studies in 2023 emphasized lightweight deep learning models suitable for real-time deployment in resource-constrained cloud environments. Optimized CNN-LSTM frameworks reported 98.5–98.7% accuracy while reducing computational overhead [9].

By 2024, attention-based and transformer-inspired architectures began emerging in intrusion detection research. These models leverage self-attention mechanisms to capture global traffic dependencies. Preliminary studies report detection efficiencies exceeding 99%, particularly on updated datasets such as CICIDS2018 [10].

E. Comparative Analysis of Model Efficiency

The progression of deep learning models for cloud intrusion detection demonstrates a clear improvement in performance over time. Table I summarizes the year-wise development and reported efficiencies.

Table I: Year-Wise Efficiency of Deep Learning-Based IDS

Year	Model	Technique Type	Dataset Used	Reported Accuracy
2015	DNN	Deep Learning	NSL-KDD	97.5%
2016	CNN	Deep Learning	NSL-KDD	98%
2017	RNN	Recurrent Neural Network	NSL-KDD	86%
2018	LSTM	Recurrent Neural Network	NSL-KDD	98.8%
2019	CNN-LSTM	Hybrid Deep Learning	CICIDS2017	99.2%
2020	Stacked LSTM	Deep Learning	UNSW-NB15	99.5%
2021	Federated LSTM	Distributed Deep Learning	CICIDS2017	97–99%
2022	CNN-LSTM + XAI	Hybrid Deep Learning	CICIDS2018	99%
2023	Lightweight CNN-LSTM	Optimized Deep Learning	UNSW-NB15	98.7%
2024	Transformer-based IDS	Attention-Based Model	CICIDS2018	>99%

Summarized Research Gaps in Cloud Data Centre IDS

Real-Time Deployment Gap

Most IDS models are tested offline on benchmark datasets. Real-time cloud deployment with low latency is still challenging.

Zero-Day and Evolving Attack Detection

Current models are trained on static datasets and struggle to detect new or unseen attacks.

Adversarial Attack Vulnerability

Deep learning IDS models can be fooled by specially crafted malicious traffic.

Lack of Explainability (Black-Box Issue)

CNN, RNN, and LSTM models do not clearly explain why a traffic flow is classified as malicious.

Scalability in Multi-Cloud Environments

Most models are tested in single-cloud setups and not distributed systems.

High Computational Cost

Deep models require heavy resources, making deployment expensive.

Cloud-Native Integration Gap

Limited research integrates IDS with containerized and microservice architectures.

III.PROPOSED METHODOLOGY

This research proposes a Lightweight Hybrid CNN-LSTM Based Intrusion Detection System (IDS) for cloud data centres. The objective is to design a model that achieves high detection accuracy while maintaining low computational complexity suitable for near real-time deployment.

The proposed model integrates:

CNN for automatic feature extraction

LSTM for temporal dependency learning

Fully connected layers for classification

The system is evaluated using benchmark intrusion detection datasets such as NSL-KDD, CICIDS2017, and UNSW-NB15.

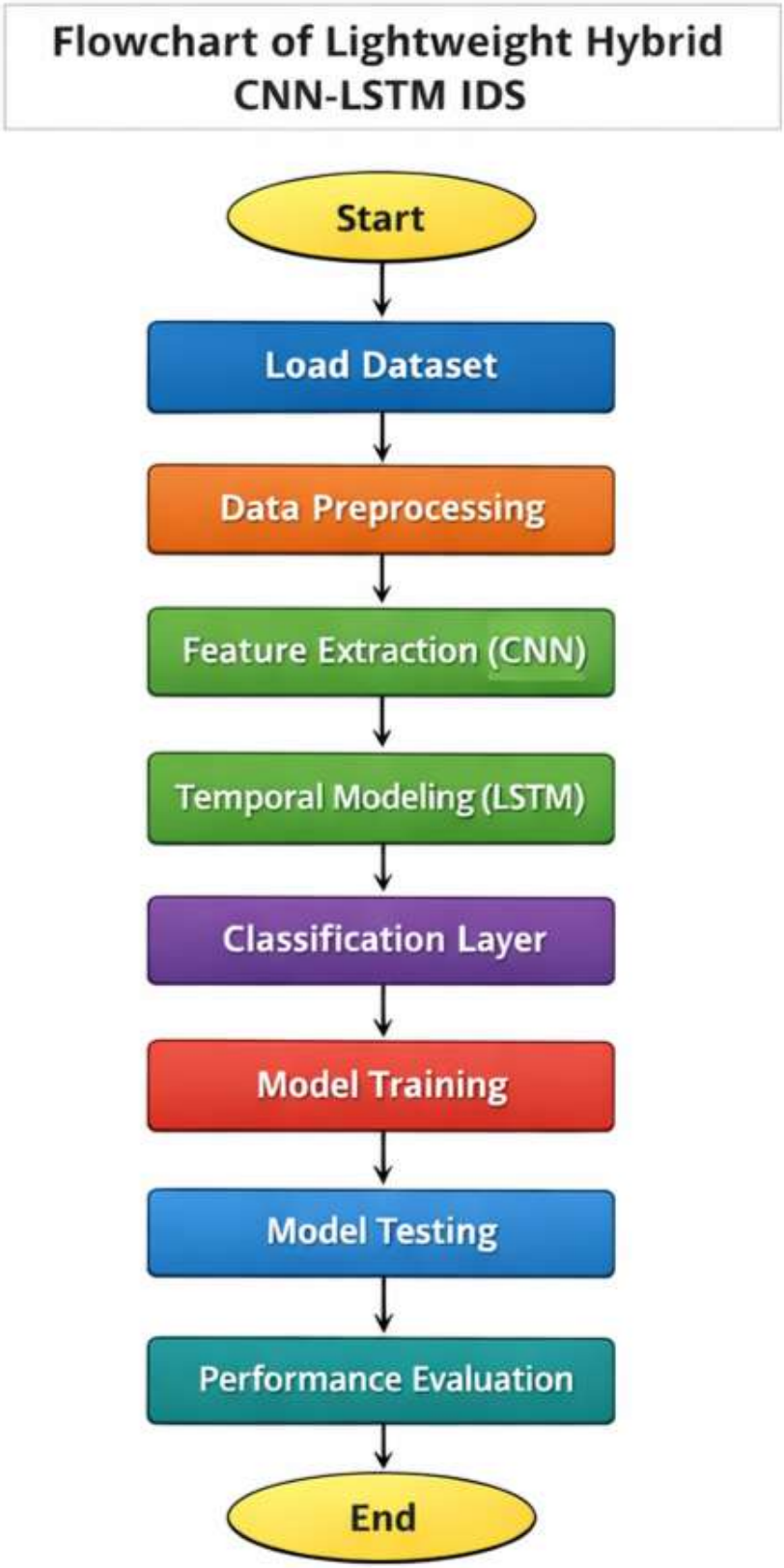
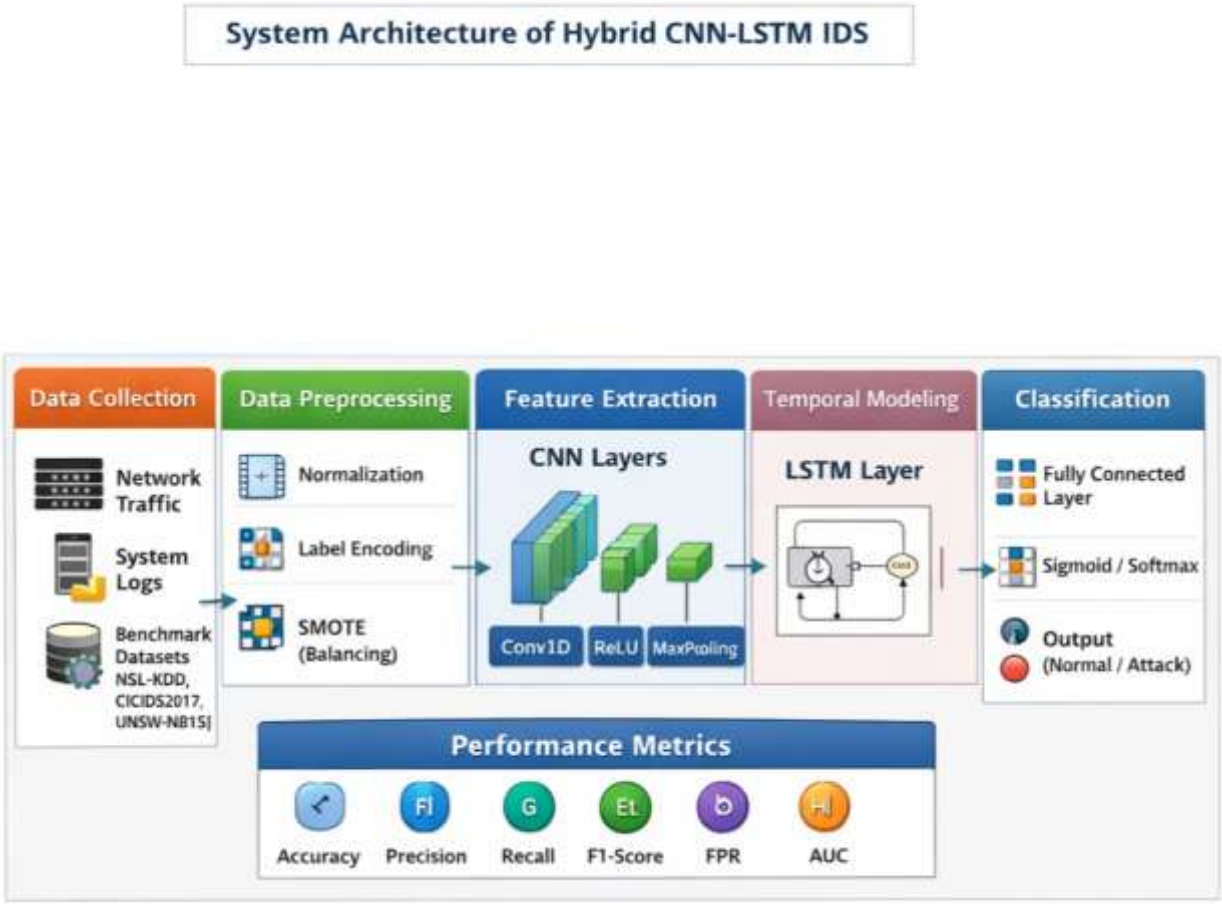

Flowchart of Lightweight Hybrid CNN-LSTM IDS
Start
Load Dataset
Data Preprocessing
Feature Extraction (CNN)
Temporal Modeling (LSTM)
Classification Layer
Model Training
Model Testing
Performance Evaluation
End

Fig. 1

Fig.2



IV.CONCLUSION

The literature review reveals a significant evolution in intrusion detection mechanisms for cloud data centres over the past decade. Traditional signature-based and anomaly-based IDS approaches were initially effective for detecting known attacks; however, their inability to adapt to dynamic cloud environments and zero-day threats limited their effectiveness.

With the advancement of deep learning, models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) have demonstrated substantial improvements in detection accuracy and robustness. CNN-based models enhanced automatic feature extraction capabilities, reducing the need for manual feature engineering. RNN models introduced temporal pattern recognition, enabling detection of sequential attack behaviors. However, standard RNN architectures suffered from vanishing gradient problems, limiting their ability to capture long-term dependencies.

The introduction of LSTM networks addressed these limitations by incorporating memory cells and gating mechanisms, significantly improving detection performance for time-dependent and multi-stage attacks. Recent hybrid architectures combining CNN and LSTM have consistently achieved accuracy levels above 99% on benchmark datasets such as NSL-KDD, CICIDS2017, and UNSW-NB15. Furthermore, emerging research focuses on federated learning, explainable AI, lightweight optimization, and transformer-based architectures to enhance scalability, interpretability, and real-time applicability.

Despite these advancements, a gap remains between high experimental accuracy in controlled environments and practical deployment in large-scale, real-time cloud data centres. Challenges such as computational complexity,

adversarial robustness, dataset imbalance, and integration with cloud-native infrastructures continue to require further investigation.

Overall, the reviewed literature establishes that hybrid deep learning models, particularly CNN-LSTM architectures, provide the most promising direction for future research in cloud intrusion detection systems. However, there is a clear need for lightweight, scalable, and explainable models that can operate efficiently in real-world cloud environments.

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