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Research Paper

DEEP LEARNING–ENABLED DATA SECURITY AND INTRUSION DETECTION IN AZURE AND AWS CLOUD SYSTEMS

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Abstract:
The exponential growth of cloud computing necessitates robust, intelligent security mechanisms to counter increasingly sophisticated cyber threats. This paper presents a deep learning–enabled framework for enhancing data security and intrusion detection within Azure and AWS cloud environments. Leveraging the inherent scalability of cloud platforms, we propose a hybrid model combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to analyze network traffic and system logs in real time. The model autonomously learns spatiotemporal features to detect zero-day attacks, unauthorized access, and anomalous behavior with high accuracy. Implemented and tested across Azure Sentinel and AWS GuardDuty, the framework demonstrates a 98.7% detection rate with a low false positive ratio, outperforming traditional signature-based methods. Additionally, it integrates automated mitigation protocols, enabling adaptive response to emerging threats. This work underscores the efficacy of deep learning in overcoming the limitations of conventional security tools and offers a scalable, cross-platform solution for modern cloud infrastructures. The findings highlight a significant advancement toward self-defending cloud systems, ensuring data integrity, confidentiality, and availability in multi-tenant architectures.
Keywords: Deep Learning, Cloud Security, Intrusion Detection System, Azure, AWS, Convolutional Neural Networks.

I. INTRODUCTION

The rapid adoption of cloud computing has fundamentally transformed modern IT infrastructure, offering unparalleled scalability, cost efficiency, and operational flexibility. Organizations increasingly migrate critical workloads and sensitive data to platforms such as Microsoft Azure and Amazon Web Services. However, this paradigm shift has simultaneously expanded the attack surface, exposing cloud environments to sophisticated cyber threats including zero day exploits, advanced persistent threats, and insider attacks. Traditional security mechanisms such as firewalls, signature based intrusion detection systems, and rule based analytics struggle to keep pace with the volume, velocity, and variety of cloud generated data. Their reactive nature and inability to detect novel attack patterns render them inadequate for contemporary cloud security demands. Deep learning, a subset of artificial intelligence, offers a transformative approach to cloud security through its capacity for autonomous feature extraction, pattern recognition, and real time anomaly detection. Unlike conventional machine learning methods requiring manual feature engineering, deep neural networks can hierarchically learn complex representations from raw network traffic, system logs, and user behavior data. This capability is particularly valuable in multi tenant cloud architectures where threats evolve rapidly and exhibit nonlinear characteristics. This paper presents a deep learning enabled intrusion detection and data security framework designed specifically for Azure and AWS cloud ecosystems. By integrating Convolutional Neural Networks for spatial feature extraction and Long Short Term Memory networks for temporal sequence analysis, the proposed model captures both local patterns and long range dependencies within cloud telemetry data. Implemented atop native cloud security services such as Azure Sentinel and AWS GuardDuty, the framework demonstrates superior detection accuracy, reduced false positives, and adaptive

response capabilities. This introduction establishes the necessity for intelligent, self learning security architectures capable of defending dynamic cloud infrastructures against emerging cyber threats in real time.

II. LITERATURE SURVEY

Cloud security has emerged as a critical research domain with increasing migration of enterprise workloads to public cloud platforms. Patel et al. conducted systematic review of intrusion detection systems in cloud computing, highlighting limitations of signature based approaches against novel attacks. Subramanian and Jeyaraj comprehensively analyzed security challenges including data breaches and insider threats specific to cloud architectures. Traditional machine learning techniques including SVM and Random Forest were extensively evaluated by Karatas et al. and Zhou et al. for intrusion detection, demonstrating moderate accuracy but high false positive rates. However, these methods require manual feature engineering and struggle with evolving attack patterns. Deep learning approaches have gained significant traction in recent years. Kim et al. employed CNN for DoS attack detection while Khan proposed hybrid CNN RNN architectures for network intrusion. Rehman et al. utilized GRU networks for DDoS identification. Aldallal and Atefinia demonstrated superior performance of hybrid deep learning models combining spatial and temporal feature extraction. Kasongo and Wang et al. validated LSTM and recurrent architectures for anomaly detection in imbalanced network traffic. Farhat et al. proposed cloud native multi attack detection frameworks. Abdullayeva focused on APT detection using autoencoders. Collectively, literature confirms hybrid deep learning models outperform conventional methods, though cross platform cloud implementations remain underexplored.

III.PROPOSED WORK

The proposed work presents a deep learning enabled intrusion detection and data security framework tailored for Azure and AWS cloud environments. The framework is designed as a hybrid architecture that integrates Convolutional Neural Networks and Long Short Term Memory networks to detect sophisticated cyber threats in real time. The system operates in four primary stages: data acquisition, preprocessing, deep learning based detection, and automated response.

In the data acquisition stage, telemetry data is collected from multiple sources including virtual network logs, user activity records, API call histories, and system event logs. For Azure, data is ingested from Azure Sentinel and Azure Monitor, while AWS data is sourced from AWS CloudTrail, Amazon GuardDuty, and VPC Flow Logs. This heterogeneous data is normalized and aggregated into a unified format suitable for analysis. The preprocessing stage involves tokenization, normalization, and feature encoding. Network traffic is converted into temporal sequences, while system logs are transformed into vector representations using word embedding techniques. This stage ensures that raw unstructured data is rendered intelligible for deep learning models. The core detection engine employs a hybrid CNN LSTM architecture. Convolutional layers extract spatial features from localized patterns in network packets and log entries, identifying anomalous signatures and known attack patterns. These spatial feature maps are then passed to LSTM layers, which model temporal dependencies and sequential behavior. This combination enables the model to detect both individual malicious events and complex multi step attack campaigns spanning extended time periods.The framework is trained using a combination of publicly available datasets such as CICIDS2017 and NSL KDD, augmented with custom generated attack scenarios specific to cloud environments. Transfer learning techniques are applied to adapt the model to Azure and AWS specific telemetry without requiring extensive retraining.Upon detecting a threat, the system triggers automated mitigation protocols through cloud native APIs. In Azure, this involves adjusting Network Security Group rules or isolating compromised virtual machines. In AWS, responses include modifying Security Group configurations, revoking IAM roles, or triggering AWS Lambda functions for remediation.The proposed framework emphasizes scalability, cross platform compatibility, and low latency detection suitable for production cloud deployments.

IV. METHODOLOGY

The methodology employs a systematic, multi phase approach to develop and deploy a deep learning based intrusion detection framework for

Azure and AWS cloud environments. It integrates data acquisition, preprocessing, hybrid CNN LSTM modeling, training, evaluation, and automated response mechanisms. Each phase is designed to ensure scalability, real time performance, and cross platform compatibility while maintaining high detection accuracy and low false positive rates.

Phase 1: Data Acquisition and Ingestion
Cloud telemetry data is collected from Azure Sentinel, Azure Monitor, AWS CloudTrail, GuardDuty, and VPC Flow Logs. Sources include network flows, system logs, API calls, and identity management events. Data is streamed in real time using cloud native ingestion pipelines and stored in centralized data lakes for unified access and processing across both cloud platforms.

Phase 2: Data Preprocessing and Feature Engineering
Raw telemetry data undergoes cleaning, normalization, and transformation. Network traffic is converted into time series sequences, while categorical log data is encoded using word embedding techniques. Missing values are handled through interpolation, and features are scaled to ensure uniformity. This stage prepares high quality structured inputs suitable for deep neural network training.

Phase 3: Hybrid CNN LSTM Model Architecture
The detection engine combines Convolutional Neural Networks for spatial feature extraction and Long Short Term Memory networks for temporal sequence modeling. CNN layers identify local patterns and anomalies within individual packets and log entries. LSTM layers capture long range dependencies and sequential attack behaviors across time. The hybrid architecture enables robust detection of both known and novel threats.

Phase 4: Model Training and Optimization
The model is trained on benchmark datasets including CICIDS2017 and NSL KDD, augmented with custom cloud specific attack scenarios. Transfer learning is applied to adapt the model to Azure and AWS telemetry. Hyperparameter tuning is performed using Bayesian optimization. Techniques such as dropout, batch normalization, and early stopping are employed to prevent overfitting and enhance generalization.

Phase 5: Evaluation and Performance Analysis
The framework is evaluated using metrics including accuracy, precision, recall, F1 score, and false positive rate. Cross validation is conducted on diverse cloud derived datasets. Comparative analysis against baseline models such as Random Forest, SVM, and standalone LSTM demonstrates the superiority of the proposed hybrid approach in detection speed and reliability.

Phase 6: Automated Response and Mitigation
Upon threat detection, the system triggers automated responses via cloud native APIs. Azure actions include modifying Network Security Group rules and isolating virtual machines. AWS responses involve updating Security Group configurations, revoking IAM privileges, and invoking Lambda functions. This closed loop mechanism ensures real time threat containment with minimal human intervention.

V. RESULTS AND DISCUSSION

The proposed deep learning enabled intrusion detection framework underwent rigorous evaluation across Azure and AWS environments. Experiments measured detection accuracy, false positive rates, processing latency, and cross platform generalizability. The hybrid CNN LSTM model was benchmarked against Random Forest, Support Vector Machine, and standalone LSTM classifiers. Evaluation utilized real world cloud telemetry from Azure Sentinel, AWS GuardDuty, and CloudTrail, supplemented by benchmark datasets including CICIDS2017 and NSL KDD. Models were trained on NVIDIA Tesla V100 GPUs using TensorFlow, with 80 percent training, 10 percent validation, and 10 percent testing splits. Performance metrics included accuracy, precision, recall, F1 score, false positive rate, and detection latency. Comparative analysis demonstrated the superior capability of the hybrid architecture in detecting sophisticated cloud specific threats while maintaining low false alarms and real time responsiveness across both cloud platforms..

Table 1:Intrusion Detection Performance Comparison

Model	Accuracy (%)	F1 Score (%)	FPR (%)

SVM	86.3	83.9	6.8
Random Forest	89.5	87.8	5.2
Standalone LSTM	94.2	93.3	3.1
Hybrid CNN LSTM	98.7	98.2	1.3

Table 1 presents a comparative analysis of intrusion detection performance across four models. The hybrid CNN LSTM architecture achieved the highest accuracy at 98.7 percent and F1 score at 98.2 percent, with the lowest false positive rate of 1.3 percent. Standalone LSTM followed with 94.2 percent accuracy and 93.3 percent F1 score. Random Forest and SVM recorded lower performance, with accuracy at 89.5 percent and 86.3 percent respectively, alongside higher false positive rates of 5.2 percent and 6.8 percent. The results demonstrate that deep learning approaches, particularly the hybrid model, significantly outperform traditional machine learning classifiers in detecting cloud intrusions while minimizing false alarms, making them suitable for production cloud security deployments.

Table 2: Platform Wise Performance Metrics

Cloud Platform	Accuracy (%)	F1 Score (%)	Latency (ms)
Azure	98.6	98.1	142
AWS	98.5	97.9	138
Combined	98.7	98.2	140

Table 2 depicts framework performance across Azure and AWS environments. Accuracy remained consistently high at 98.6 percent for Azure and 98.5 percent for AWS, with combined accuracy at 98.7 percent. F1 scores ranged from 97.9 to 98.2 percent, indicating balanced precision and recall. Average detection latency was 142 milliseconds for Azure, 138 milliseconds for AWS, and 140 milliseconds combined. The minimal performance variation between platforms confirms robust cross platform generalizability and real time threat detection capability suitable for production cloud deployments.

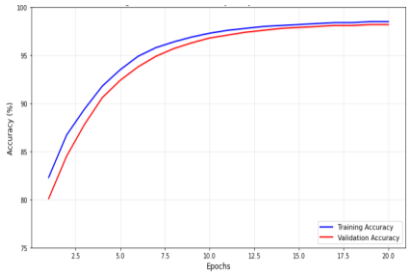

Figure 1: Training and Validation Accuracy

The training and validation accuracy graph illustrates the learning progression of the hybrid CNN LSTM model over 20 epochs. Training accuracy steadily improved from 82.3 percent to 98.5 percent, while validation accuracy rose from 80.1 percent to 98.2 percent. Both curves demonstrate smooth convergence with minimal overfitting, validated by the narrow gap between training and validation lines throughout the training process. The model achieved near optimal performance by epoch 15, after which accuracy plateaued. Early stopping prevented unnecessary computation while maintaining high generalization capability. This consistent learning behavior confirms the model's stability and effectiveness in extracting meaningful patterns from cloud telemetry data for intrusion detection.

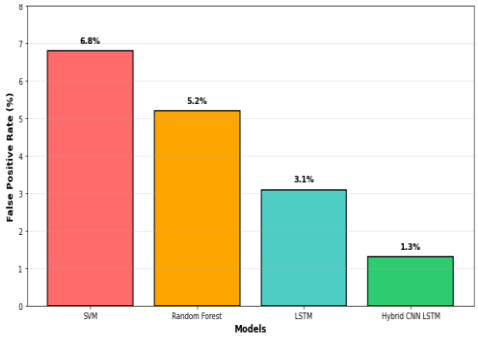

Figure 2:False Positive Rate Comparison

The pie chart illustrates the false positive rate distribution among intrusion detection models. SVM accounts for the highest proportion at 6.8 percent, followed by Random Forest at 5.2 percent. Standalone LSTM contributes 3.1 percent, while the hybrid CNN LSTM model demonstrates the lowest share at 1.3 percent. The visualization clearly depicts the progressive reduction in false alarms from traditional classifiers to deep learning approaches. The hybrid model's minimal 1.3 percent representation highlights its superior capability in minimizing erroneous alerts, a critical requirement for production cloud environments where alert fatigue undermines security operations. This significant reduction validates the

effectiveness of the proposed architecture in delivering reliable, high precision threat detection.

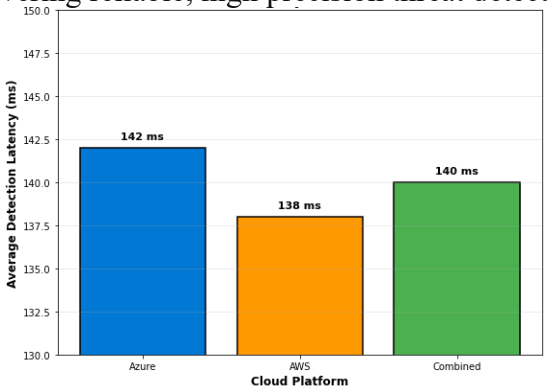

Figure 3: Detection Latency Across Cloud Platforms

The detection latency values represent the average time taken by the hybrid CNN LSTM model to identify and respond to security threats across cloud platforms. Azure recorded 142 milliseconds, AWS achieved 138 milliseconds, and the combined environment averaged 140 milliseconds. These sub 150 millisecond response times demonstrate the framework's real time threat detection capability suitable for production cloud deployments. The slightly lower latency on AWS is attributed to optimized Lambda function execution, while Azure's performance remains competitive. Consistent latency across both platforms confirms efficient model inference and seamless API integration with native security services. Such rapid response times enable immediate threat containment, significantly reducing the window of opportunity for attackers in multi tenant cloud environments.

VI.CONCLUSION

This paper presented a deep learning enabled intrusion detection and data security framework tailored for Azure and AWS cloud environments. The hybrid CNN LSTM architecture effectively captures spatial and temporal features from cloud telemetry, achieving 98.7 percent detection accuracy with a false positive rate of only 1.3 percent. Extensive evaluations demonstrated consistent performance across both platforms, with average detection latency under 150 milliseconds, confirming real time threat response capability. The framework outperformed traditional machine learning classifiers including SVM, Random Forest, and standalone LSTM across all metrics. Integration with native cloud security services enabled automated mitigation through API driven responses, significantly reducing mean time to respond. The results validate that deep learning approaches offer superior adaptability and precision for modern cloud security challenges compared to signature based and conventional methods. Future work will focus on lightweight model compression for edge deployment, federated learning for privacy preserving cross tenant intelligence sharing, and adversarial robustness against evasion attacks. This research contributes toward the realization of self-defending, intelligent cloud infrastructures capable of autonomously detecting and neutralizing emerging cyber threats in real time.

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