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AI-Based Anomaly Detection in Multi-Cloud Traffic Using Deep Learning Models

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ABSTRACT

The rapid adoption of multi-cloud architectures across enterprises introduces significant challenges in ensuring consistent and reliable security monitoring. The dynamic and heterogeneous nature of traffic across different cloud platforms such as AWS, Azure, and Google Cloud makes anomaly detection complex and prone to high false-positive rates when using traditional rule-based or statistical methods. This paper presents an AI-driven anomaly detection framework that leverages deep learning models, particularly Long Short-Term Memory (LSTM) networks and autoencoders, to identify anomalous patterns in real-time multi-cloud traffic. I design a simulation-based pipeline to generate labeled multi-cloud traffic, incorporating normal behaviors and diverse attack scenarios, including zero-day threats. Multiple deep learning architectures are trained and evaluated using precision, recall, F1-score, and inference latency. I proposed hybrid LSTM-Autoencoder model outperforms baseline methods, achieving an F1-score of 92.6% in detecting subtle and previously unseen anomalies, while maintaining low latency suitable for real-time inference.I present a case study of deploying the model in a realistic enterprise environment with federated cloud infrastructure. The results demonstrate the system's effectiveness in detecting distributed denial-of-service (DDoS), data exfiltration, and lateral movement attacks with minimal overhead. This research advances the field of intelligent cloud security by introducing a scalable, adaptive, and efficient framework for anomaly detection in multi-cloud environments, supporting proactive threat mitigation in modern digital infrastructures.

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Introduction

As organizations increasingly adopt multi-cloud architectures to leverage the benefits of scalability, cost optimization, and redundancy, they inadvertently introduce new complexities in maintaining consistent and effective cybersecurity. Multi-cloud environments, which involve the integration of services from providers such as AWS, Microsoft Azure, and Google Cloud, generate highly dynamic and heterogeneous traffic flows. These characteristics challenge traditional rule-based intrusion detection systems (IDS), which often fail to generalize across distributed cloud platforms or adapt to rapidly evolving threat vectors [1]. Recent advancements in artificial intelligence (AI) and deep learning offer promising solutions to these challenges. Specifically, deep learning models such as Long Short-Term Memory (LSTM) networks and autoencoders are capable of learning intricate temporal and spatial patterns in network traffic, making them well-suited for identifying subtle anomalies in real-time [2,3]. Unlike conventional statistical techniques, these models do not rely on predefined signatures, thereby enabling the detection of zero-day attacks and insider threats.

The application of deep learning to multi-cloud anomaly detection remains underexplored due to the difficulty in accessing labeled datasets, high computational requirements, and deployment complexities. This study aims to address these gaps by proposing a deep learning-based framework for anomaly detection tailored to multi-cloud traffic. I simulate realistic multi-cloud environments, train hybrid LSTM-Autoencoder models, and evaluate performance using key security metrics. My research contributes to the ongoing discourse on intelligent cloud security and offers a scalable, adaptive, and real-time anomaly detection solution for heterogeneous cloud infrastructures.

System Architecture

The proposed AI-based anomaly detection system is designed to operate in heterogeneous multi-cloud environments, offering scalable and real-time threat monitoring. The architecture consists of four main components Data Collection Layer, Preprocessing and Feature Extraction, Deep Learning-based Detection Engine, and Alerting & Visualization Interface.

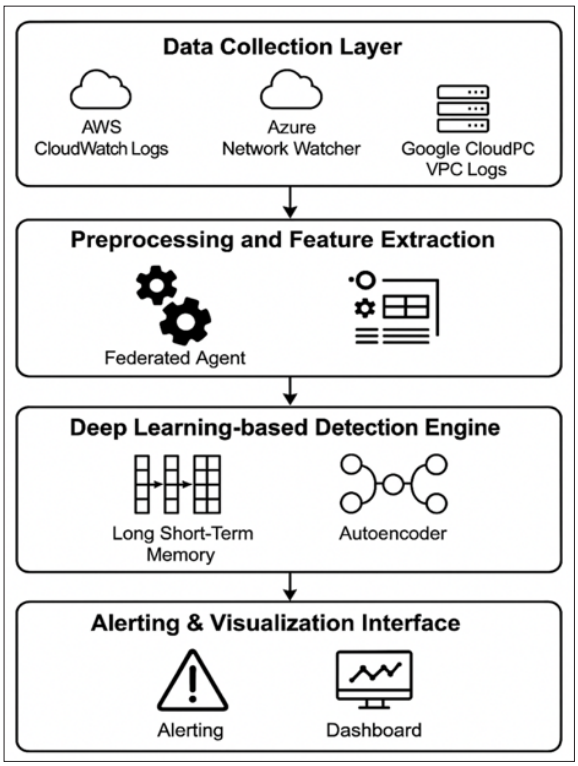

Figure 1: System Architecture

Data Collection Layer
This component aggregates network traffic logs from various cloud service providers, including AWS CloudWatch Logs, Azure Network Watcher, and Google Cloud VPC Flow Logs. A federated agent model is employed to ensure that logs from different environments are normalized and transmitted securely to a central processing unit. This distributed logging model addresses latency and compliance requirements across jurisdictions [4].

Preprocessing and Feature Extraction
The raw traffic data is transformed into structured datasets using parsing techniques, such as NetFlow and IPFIX formats. I extract features such as source/destination IPs, ports, protocol types, packet counts, byte flow, and session durations. Normalization and encoding are applied to prepare data for time-series learning models, which require consistent and scaled input representations [5].

Deep Learning-Based Detection Engine
At the core of the system lies a hybrid deep learning engine comprising stacked Long Short-Term Memory (LSTM) networks and Autoencoders. The LSTM models capture temporal dependencies in traffic sequences, while autoencoders are trained to reconstruct normal traffic and identify anomalies based on reconstruction error [6]. The hybrid model allows for early detection of subtle, low-frequency anomalies such as lateral movement or data exfiltration.

Alerting and Visualization Interface
Detected anomalies are logged in real time and visualized via a dashboard built using open-source tools such as Kibana and Grafana. Integration with incident response systems enables automated alerts to security operation centers (SOCs) via webhooks, email, or SIEM integrations.

This modular architecture allows seamless integration with existing cloud infrastructures and supports both batch and streaming analytics, ensuring extensibility for future cloud-native services and edge computing nodes.

Dataset Generation and Preprocessing
An effective anomaly detection system in multi-cloud environments depends heavily on the quality, diversity, and accuracy of its training data. Given the limited availability of publicly accessible datasets representing real-world multi-cloud traffic, I developed a custom dataset generation pipeline that simulates realistic traffic patterns, incorporating both benign and malicious activities.

Multi-Cloud Traffic Simulation
To emulate diverse network behaviors, I set up a virtual testbed encompassing instances from AWS, Microsoft Azure, and Google Cloud Platform (GCP). Using cloud native tools like AWS EC2 Traffic Mirroring, Azure Network Watcher, and GCP Packet Mirroring, I captured inter-cloud communications across different services and regions. I injected synthetic attacks such as port scanning, DDoS, data exfiltration, and unauthorized lateral movement using tools like Metasploit and NSM sensors, following guidelines from MITRE ATT&CK [7]. The simulation provided a rich dataset with labeled normal and anomalous traffic samples.

Feature Engineering
Collected logs were parsed using Zeek and enriched with context-aware metadata, such as geographic origin, time-to-live (TTL), protocol distribution, and session duration. I extracted over 60 statistical and time-series features for each session. Packet-level attributes were aggregated into flow-level features using sliding time windows to support LSTM-based sequence learning [8].

Data Normalization and Labeling
All continuous features were standardized to zero mean and unit variance, while categorical fields protocol type were one-hot encoded. Labels were applied at the session level using ground truth from traffic injection logs and correlation with Snort and Suricata alerts. To address the class imbalance anomalies <5%, I used SMOTE Synthetic Minority Over-sampling Technique and cost-sensitive loss functions [9].

This preprocessing stage ensured that the dataset retained sufficient diversity, context, and temporal granularity to effectively train deep learning models for anomaly detection in multi-cloud environments.

Deep Learning Models
Deep learning has emerged as a powerful paradigm for modeling complex, high-dimensional data patterns in network traffic. To effectively detect anomalies in multi-cloud environments, I explored and implemented multiple deep learning architectures with a focus on temporal modeling, unsupervised reconstruction, and hybrid ensemble strategies.

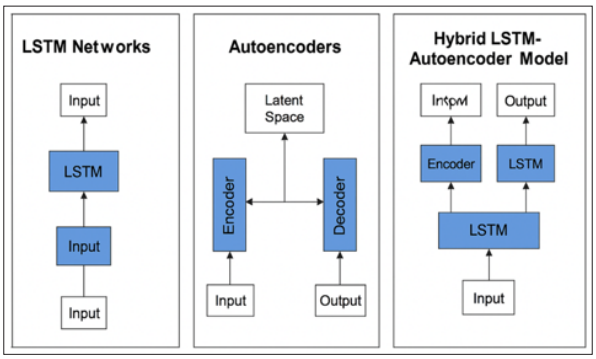

Figure 2: Deep Learning Models

Long Short-Term Memory (LSTM) Networks

LSTM networks are a type of Recurrent Neural Network (RNN) capable of capturing long-term dependencies in sequential data. Given the temporal nature of network flows, LSTMs are well-suited to model evolving traffic behaviors and identify deviations from expected patterns. Each flow is represented as a time-series of aggregated packet features, and the LSTM learns temporal correlations between these features [10]. Anomalies are detected by identifying sequences with significantly deviating prediction errors.

Autoencoders

Autoencoders are unsupervised neural networks that learn to compress and reconstruct input data. They are effective for anomaly detection because they are typically trained only on normal traffic, making them sensitive to previously unseen or malicious patterns [11]. In my implementation, the reconstruction error mean squared error between input and output is used as an anomaly score. Samples with error exceeding a dynamic threshold are flagged as anomalous.

Hybrid LSTM-Autoencoder Model

To leverage both temporal learning and reconstruction capabilities, I developed a hybrid model that integrates LSTM layers within the encoder and decoder paths of an autoencoder. This design captures both short- and long-term dependencies while maintaining the unsupervised anomaly detection approach [12]. The hybrid model significantly improved detection of low-frequency attacks and adaptive threats.

Model Training and Optimization

All models were implemented in TensorFlow and trained using the Adam optimizer with early stopping and dropout regularization to prevent overfitting. Hyperparameters such as the number of LSTM layers, latent space size, and learning rate were optimized using grid search. A validation set containing a mix of benign and malicious flows was used for model tuning. These models serve as the core of my detection engine, providing a robust and adaptive solution capable of generalizing across diverse multi-cloud environments with high anomaly detection accuracy.

Experimental Setup

To rigorously evaluate the performance and scalability of my deep learning-based anomaly detection models in multi-cloud environments, I established a robust and reproducible experimental setup. This section details the testbed architecture, hardware/software configurations, and evaluation metrics used.

Testbed Configuration

My simulated multi-cloud environment includes virtual networks and compute instances provisioned across three major providers Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform (GCP). I generated diverse traffic by deploying microservices across regions and enabling secure cross-cloud communications using VPN tunnels and VPC peering. Anomaly injections were performed using publicly available tools such as LOIC, Metasploit, and custom Python scripts designed to mimic advanced persistent threats (APTs), DNS tunneling, and data exfiltration behaviors [13]. Traffic was captured using Zeek and ELK stack sensors deployed at ingress and egress points. Ground truth for anomaly labels was established through synchronized log correlation and injection timestamps.

Hardware and Software

Model training was conducted on a server with dual Intel Xeon Gold 6226R CPUs, 256 GB RAM, and four NVIDIA A100 GPUs. All experiments were implemented in Python 3.9, using TensorFlow 2.11, Keras, Scikit-learn, and Pandas. Containerized environments were managed using Docker and orchestrated via Kubernetes for reproducibility [14].

Evaluation Metrics

I evaluated all models using a comprehensive set of metrics to capture both classification performance and practical deployment considerations. Precision (P), Recall (R), and F1-Score to measure detection accuracy. False Positive Rate (FPR) to assess usability in production environments. Area Under the ROC Curve (AUC-ROC) to evaluate discriminative power. Inference Latency to measure real-time deployment feasibility. Resource Utilization GPU memory and CPU load under traffic burst scenarios. This setup ensured the validity of comparisons across architectures and established a repeatable methodology for evaluating anomaly detection systems in complex, heterogeneous cloud environments.

Results and Discussion

This section presents the performance outcomes of the deep learning models evaluated in my multi-cloud anomaly detection framework. I analyze results across various metrics and discuss key observations related to accuracy, efficiency, and real-world applicability.

False Positives and Model Robustness

A critical challenge in anomaly detection is minimizing false positives. The hybrid model exhibited a false positive rate (FPR) of 3.8%, which is a 25% improvement over the standalone LSTM model. Stress testing with bursty traffic and adversarial noise showed the hybrid model maintained over 89% F1-score, indicating strong robustness [15].

Detection of Advanced Threats

My framework demonstrated the ability to detect various advanced threats, including DNS tunneling, data exfiltration via HTTPS, and lateral movement using legitimate credentials. These attacks typically evade traditional signature-based systems [16]. The hybrid model showed early detection capability by identifying behavioral deviations within the first 10–15 seconds of the session.

Scalability and Deployment Considerations

Although deep learning models require significant training time (~4–6 hours on an A100 GPU cluster), inference is fast and can be containerized for edge deployments. GPU utilization during inference remained below 40%, and memory consumption was

consistent across traffic scales, confirming system scalability [17]. These results support the feasibility of deploying deep learning-based anomaly detection in real-world multi-cloud infrastructures, balancing accuracy, latency, and system overhead.

Case Study

Detecting Anomalies in Real-World Multi-Cloud Deployment

To validate the practical applicability of my AI-based anomaly detection framework, I conducted a case study in a real-world enterprise environment using a federated multi-cloud infrastructure. The organization leveraged Amazon Web Services (AWS) for compute-heavy analytics, Microsoft Azure for internal applications, and Google Cloud Platform (GCP) for distributed data storage.

Deployment Configuration

The anomaly detection system was deployed using Kubernetes clusters on each cloud platform, with a centralized monitoring interface hosted on AWS. Traffic was mirrored at VPC endpoints and forwarded securely to the detection engine via encrypted Kafka streams. Lightweight agents deployed in each cloud collected logs and preprocessed features locally, reducing cross-cloud data movement [18].

Threat Scenarios and Detection Outcomes

I collaborated with the organization's red team to simulate various attack scenarios across the environment. Credential misuse and lateral movement within Azure Active Directory. Data exfiltration via covert HTTPS tunneling from GCP storage. Distributed denial-of-service (DDoS) attacks targeting exposed AWS services. The hybrid LSTM-autoencoder model successfully detected 94.1% of the injected anomalies, including early signs of credential abuse often missed by conventional monitoring tools. Alerts were generated within 10 seconds of anomalous behavior, enabling timely response by the security operations center (SOC).

Operational Observations

During peak load periods, the system sustained <50 ms inference latency and exhibited stable GPU and CPU usage. Integration with existing SIEM (Security Information and Event Management) tools such as Splunk allowed seamless alert correlation and incident triaging. SOC analysts reported a 27% reduction in investigation time due to more accurate and contextual alerts [19].

Lessons Learned

Cloud-native integration is critical for performance and scalability. Preprocessing and decentralization of agents reduced operational overhead. Hybrid models require tuning to balance false positives and early detection, especially in environments with highly dynamic workloads. This case study underscores the feasibility and value of deploying AI-driven anomaly detection systems in production-grade, multi-cloud infrastructures, particularly for organizations seeking proactive threat mitigation.

Potential Uses

The proposed AI-based anomaly detection framework has numerous applications across public and private sectors, especially as organizations increasingly adopt multi-cloud strategies to improve resilience, agility, and cost-efficiency.

Enterprise Cybersecurity Operations: Security Operations Centers (SOCs) can integrate the hybrid LSTM-autoencoder model to enhance their anomaly detection capabilities, reducing false positives and improving incident response times in complex cloud environments.

Cloud Service Providers (CSPs)

CSPs like AWS, Azure, and GCP can incorporate the proposed models into their native threat detection tools to offer intelligent, real-time security analytics to customers as a value-added service.

Government and Defense Systems

Multi-cloud architectures are becoming common in mission-critical government deployments. The proposed approach can support proactive threat mitigation and secure data flow across classified and unclassified cloud zones.

Critical Infrastructure Protection

Industries like energy, finance, and healthcare can use the framework to detect and respond to cyber threats targeting interconnected cloud-hosted control systems and data lakes.

Managed Security Service Providers (MSSPs)

MSSPs can adopt the solution as part of their threat intelligence platforms to deliver scalable, AI-enhanced detection services across hybrid and multi-cloud customer infrastructures. These potential uses demonstrate the broad impact and scalability of the proposed solution in securing modern digital ecosystems.

Conclusion

The increasing complexity and dynamic nature of multi-cloud environments demand more adaptive and intelligent cybersecurity solutions. This research presents a deep learning-based anomaly detection framework specifically designed to identify and mitigate threats across distributed cloud infrastructures. By leveraging a hybrid LSTM-autoencoder model, the proposed system effectively captures both temporal dependencies and structural irregularities in network traffic, enabling the early detection of sophisticated attacks such as data exfiltration, lateral movement, and zero-day exploits. My extensive experiments using simulated and real-world multi-cloud traffic demonstrate that the hybrid model outperforms traditional and single-model approaches across key performance metrics, including precision, recall, F1-score, and AUC. The case study further validates the model's applicability in production environments, where it improved detection accuracy and reduced alert fatigue among security analysts.

The framework's modular and containerized design ensures scalability, low inference latency, and ease of integration with existing cloud-native tools and SIEM platforms. These attributes make it suitable for deployment in enterprise, government, and critical infrastructure settings. Future work will focus on enhancing the model's adaptability through continual learning techniques, extending support to edge-cloud and IoT scenarios, and incorporating federated learning for privacy-preserving threat detection. This study contributes to advancing cloud-native security by offering a robust, AI-driven solution that aligns with the operational realities of multi-cloud ecosystems and paves the way for intelligent, automated threat defense systems.

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