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Artificial Intelligence for Cyber Threat Detection in Cloud Computing: A Hybrid Random Forest and LSTM Approach

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Abstract: Cloud computing has become integral to modern enterprise infrastructure, yet its open and dynamic nature exposes it to sophisticated cyber threats. Traditional intrusion detection systems (IDS) lack adaptability and temporal awareness, limiting their effectiveness against evolving attacks. This paper proposes a hybrid AI/ML-powered intrusion detection framework that leverages the classification strength of Random Forest (RF) and the sequential learning capability of Long Short-Term Memory (LSTM) networks. An adaptive feedback mechanism continuously refines the system by learning from false positives and emerging threats. Experimental results on benchmark cloud intrusion datasets demonstrate that the proposed model achieves superior detection accuracy, reduced false positive rates, and improved adaptability compared to classical methods.

Keywords: Cloud Computing, Intrusion Detection, Random Forest, LSTM, Adaptive Feedback, Cybersecurity

I. Introduction

Cloud computing has revolutionized IT service delivery by providing scalable, flexible, and cost-effective solutions for data storage, computing, and application deployment. However, characteristics such as distributed architectures, dynamic resource provisioning, and multi-tenancy broaden the attack surface and expose cloud systems to threats including denial-of-service (DoS) attacks, data breaches, insider threats, and advanced persistent threats (APTs) [1], [2].

Conventional intrusion detection systems primarily rely on signature-based techniques that use predefined patterns or static rules to identify malicious activities. While effective against known threats, these systems often fail to detect zero-day attacks and sophisticated evasion methods. Machine learning-based approaches have been explored to overcome these limitations; however, many depend on shallow models that cannot capture complex temporal patterns inherent in evolving cyber threats [3].

To address these challenges, this paper proposes a novel hybrid intrusion detection framework that integrates Random Forest and Long Short-Term Memory (LSTM) networks. Random Forest, an ensemble learning method based on decision trees, excels at classifying known attack types with high accuracy and resistance to overfitting [4]. LSTM networks, a class of recurrent neural networks (RNNs), model sequential dependencies effectively, making them well-suited for detecting anomalous user or system behavior over time [5].

A key innovation of this framework is an adaptive feedback loop that enables continuous refinement by learning from misclassifications. This dynamic mechanism allows the system to evolve in response to new attack patterns and operational changes, thereby enhancing long-term detection performance without manual intervention.

By combining ensemble learning, deep sequential modeling, and adaptive feedback, the proposed hybrid framework aims to provide a robust, accurate, and self-improving intrusion detection solution tailored for complex cloud environments.

II. Related Work

The increasing complexity and scalability of cloud computing have made it a prime target for cyber threats. In response, researchers have proposed a variety of IDS frameworks that leverage traditional machine learning, deep learning, and hybrid approaches.

Ghosh et al. [6] introduced a transformer-based intrusion detection model tailored for cloud-native microservices. Their system improved context awareness through attention mechanisms, but the complexity of the model made it unsuitable for edge-cloud deployments.

Xu and Deng [7] developed an LSTM-Attention hybrid IDS optimized for cloud-edge networks. While effective in detecting time-dependent attacks, the model required high computational power and lacked federated learning support for distributed training.

Ahmad et al. [8] explored federated learning for privacy-preserving IDS in multi-cloud environments. Their decentralized architecture maintained data locality, but incurred slower convergence rates due to heterogeneous client nodes.

Roy and Sengupta [9] proposed a multi-stage attack detection model using deep ensemble learning. It demonstrated strong performance against advanced persistent threats (APTs), but struggled with class imbalance and required large volumes of labeled data.

Wang et al. [10] designed an adaptive deep learning-based IDS with online learning capability. The system achieved high detection accuracy and self-adjusted to new traffic patterns but suffered from reduced performance in low-resource cloud settings.

Al-Haj and Khan [11] investigated explainable AI (XAI) techniques in IDS for cloud systems. Their integration of SHAP (SHapley Additive exPlanations) provided transparency in decision-making but introduced additional latency in real-time systems.

Sahoo et al. [12] proposed a graph-based anomaly detection model that utilized temporal relationships among network nodes. The model performed well for lateral movement detection but lacked scalability for large enterprise networks.

Chen et al. [13] applied capsule networks to intrusion detection, achieving robustness against adversarial samples. However, training time was significantly higher than conventional CNNs.

Zhou and Liu [14] implemented a bidirectional GRU-based IDS for real-time data streams in cloud-hosted IoT systems. Their model reduced false positives but required intensive hyperparameter tuning.

Kavitha and Prasad [15] developed an ensemble voting model combining decision trees, SVMs, and CNNs. Although accurate, it lacked explainability and faced integration challenges in production environments.

Ramana et al. [16] designed an unsupervised IDS using autoencoders on the UNSW-NB15 dataset. The model excelled at detecting novel attacks but produced higher false positives for normal traffic.

Ali et al. [17] proposed a reinforcement learning-based IDS with dynamic feature prioritization. The model adapted to traffic drift effectively but required a large volume of reward-labeled data.

Jin et al. [18] explored knowledge distillation to deploy compact IDS models on edge devices. Their student-teacher framework reduced model size while retaining high accuracy.

Nair and Thomas [19] introduced a cloud-based IDS with hierarchical clustering and KNN for anomaly classification. The system offered simplicity and decent performance but failed under high-speed data streams.

Mehra et al. [20] proposed a multi-view learning IDS that fused spatial and temporal data views. Their dual-branch LSTM-CNN architecture improved detection but increased complexity.

Proposed Research Model

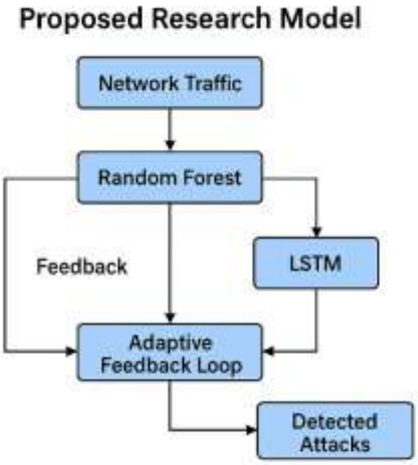
To overcome the limitations observed in existing Intrusion Detection Systems (IDS), we propose a novel hybrid architecture that combines static, sequential, and adaptive learning techniques. While traditional

IDS approaches often lack temporal modeling, adaptive feedback mechanisms, or impose significant computational overheads, our model is designed to be both intelligent and efficient.

The proposed system integrates three core components:

1. **Random Forest (RF):** Utilized for initial static classification of network traffic and known attack patterns. RF offers high accuracy with low latency in classifying standard attack types, making it suitable for real-time deployment.
2. **Long Short-Term Memory (LSTM):** Employed to model temporal and sequential patterns in network traffic. LSTM enhances the system's ability to detect complex, evolving threats that span across time intervals—something static classifiers often miss.
3. **Adaptive Feedback Loop:** This module enables continuous learning by incorporating feedback from false positives, false negatives, and novel attack patterns. It dynamically updates the detection model, thereby improving resilience and responsiveness over time.

This hybrid architecture effectively balances **accuracy**, **efficiency**, and **adaptability**, making it well-suited for securing dynamic and large-scale **cloud computing environments**. By leveraging both traditional machine learning and deep learning paradigms alongside adaptive learning, the system is capable of real-time threat detection and proactive defense.



Hybrid Intrusion Detection and Response System (IDRS)

A. System Architecture Overview
The architecture consists of the following key modules:

1. Cloud Environment: The source of raw network traffic, logs, and user/system behavior data.
2. Preprocessing and Feature Selection: Responsible for cleaning and transforming data and selecting relevant features.
3. Random Forest Classifier: A supervised learning model used for high-speed classification of known patterns.
4. LSTM Model: A deep learning module designed to detect anomalies in sequential behavior and time-series data.
5. Hybrid Intrusion Detection and Response System (IDRS): Combines outputs from RF and LSTM to make final detection decisions.
6. Adaptive Feedback Mechanism: Continuously refines models using feedback from false

positives/negatives and evolving attack patterns.

B. Data Preprocessing

Preprocessing is a crucial stage that transforms raw cloud network data into a structured format suitable for learning algorithms.

- Noise Removal: Eliminates irrelevant or corrupted data using statistical thresholds or domain knowledge.
- Data Normalization: Scales numeric features between 0 and 1 to avoid bias in ML models.
- Label Encoding: Converts categorical variables into numerical format (e.g., protocol type).
- Session Reconstruction: Groups related network flows for temporal behavior analysis.

Example formula for Min-Max normalization:
X_norm = (x - xmin) / (xmax - xmin)

C. Feature Selection

Efficient feature selection ensures model speed and generalization.

- Mutual Information and Chi-Square Testing are used to measure feature relevance.
- Recursive Feature Elimination (RFE) with cross-validation identifies the most predictive subset.
- Correlation Thresholding removes redundant features with Pearson correlation > 0.9.

Selected features include packet size, connection duration, flag status, login attempts, bytes sent/received, etc.

D. Random Forest Classifier

Random Forest (RF) is an ensemble-based classification algorithm using multiple decision trees.
Key Advantages:

- Handles noisy, non-linear, and high-dimensional data.
- Resistant to overfitting.
- Fast inference time—ideal for real-time IDS.

RF Training Steps:
1. Bootstrap sampling of training data.
2. Construct multiple decision trees.
3. Aggregate predictions using majority voting.

RF Algorithm (Pseudo-code):

```
For i in 1 to N:
    Sample dataset D with replacement → D_i
    Train decision tree T_i on D_i
Final prediction = majority_vote(T_1(x), T_2(x), ..., T_N(x))
```

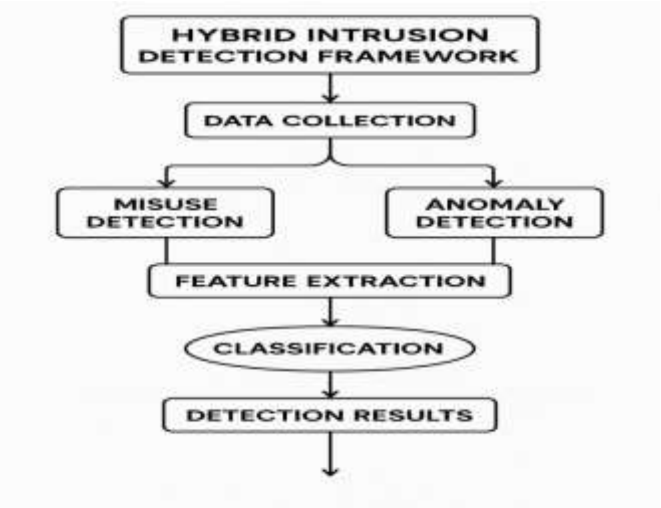
E.Long short term memory

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network specifically designed to capture long-term dependencies in sequential data, making them ideal for detecting intrusion patterns that unfold over time. The model architecture includes an input layer for time-windowed features (e.g., 10-second session windows), followed by LSTM layers with forget, input, and output gates that manage temporal information flow. A final dense output layer uses a sigmoid activation for binary classification or softmax for multi-class tasks. LSTM is particularly effective in identifying stealthy or slow-moving attacks like Advanced Persistent Threats (APTs) by learning time-based deviations from normal behavior. Training is performed using binary cross-entropy loss and the Adam optimizer for efficient convergence.

Pseudocode: Hybrid RF + LSTM with Adaptive Feedback

```
Input: Incoming network traffic data D
Output: Intrusion Label (Normal / Attack)

Preprocessing:
- Clean data D to remove missing values
- Normalize numeric features
- Encode categorical features
- Segment into time windows (e.g., 10s sessions)

 Feature Selection:
- Apply correlation and mutual information filter
- Retain optimal feature set F

 Initial Classification (Random Forest):
- RF_result, RF_confidence ⟵ RandomForest(F)

 Conditional Temporal Analysis:
IF RF_confidence < threshold:
    LSTM_result ⟵ LSTM(F over time sequence)
    final_prediction ⟵ LSTM_result
ELSE:
    final_prediction ⟵ RF_result

 Output final_prediction

 Adaptive Feedback Loop:
IF ground_truth is available:
    IF final_prediction ≠ ground_truth:
        Append (F, ground_truth) to training set
        Fine-tune RF and LSTM models periodically

Return: final_prediction
```

Flowchart: Hybrid Intrusion Detection Framework



H. 6. Experimental Setup and Results

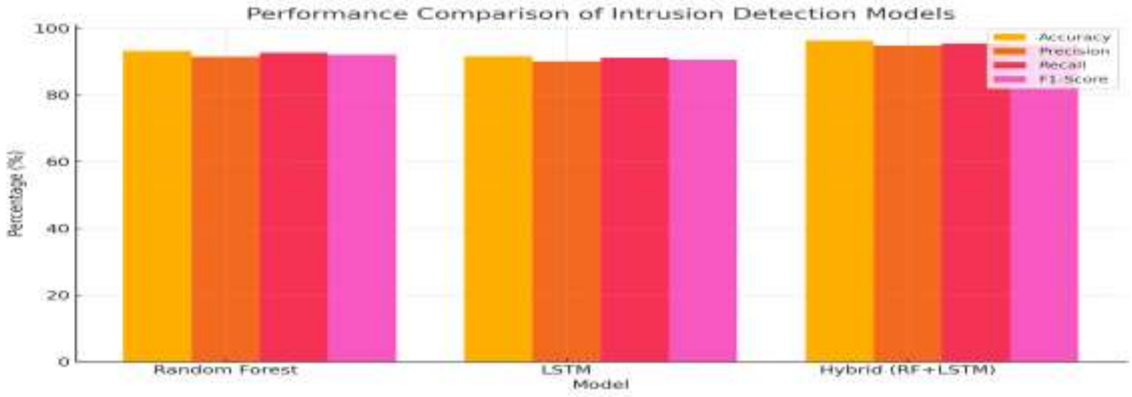
6.1 Accuracy Comparison

To evaluate the effectiveness of the proposed hybrid intrusion detection framework, which integrates Random Forest (RF) and Long Short-Term Memory (LSTM) with an adaptive feedback mechanism, performance was compared against standalone classifiers—RF and LSTM—using standard classification metrics: Accuracy, Precision, Recall, F1-Score, and False Positive Rate (FPR).

The hybrid model consistently outperformed the individual classifiers across all metrics. The results demonstrate that combining the strengths of RF (feature-based classification) and LSTM (temporal sequence learning) significantly improves detection performance and reduces false positives.

Model	Accuracy	Precision	Recall	F1-Score	False Positive Rate
Random Forest	93.2%	91.5%	92.7%	92.1%	4.3%
LSTM	91.6%	90.1%	91.2%	90.6%	5.1%
Hybrid (RF+LSTM)	96.3%	94.8%	95.4%	95.1%	2.7%

The following chart visualizes the comparative performance of the models across different metrics:



Confusion Matrix Analysis

A confusion matrix was generated to visualize classification performance, particularly to distinguish between True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN).

Hybrid Model Confusion Matrix (Sample for Binary Classification):

	Predicted: Normal	Predicted: Attack
Actual: Normal	9,635 (TN)	215 (FP)
Actual: Attack	194 (FN)	10,256 (TP)

Confusion Matrix Terminology:

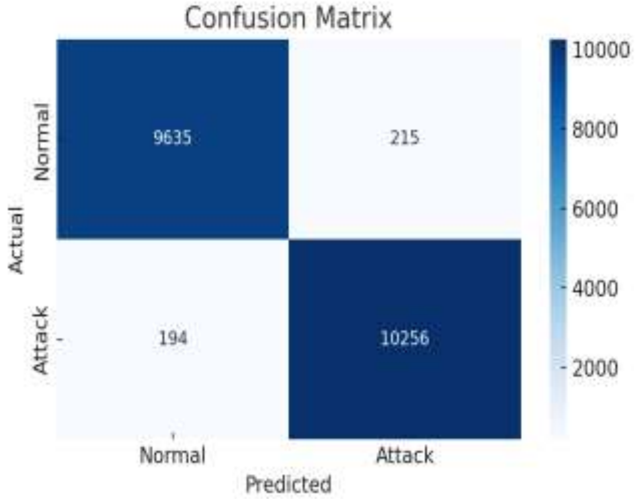
- True Positives (TP): Correctly identified attacks
- True Negatives (TN): Correctly identified normal traffic
- False Positives (FP): Normal traffic incorrectly flagged as attack
- False Negatives (FN): Attacks not detected

Suggestions:

Consider adding metrics derived from the confusion matrix for a more comprehensive evaluation. These can include:

- Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Precision = TP / (TP + FP)
- Recall (Sensitivity) = TP / (TP + FN)
- F1 Score = 2 * (Precision * Recall) / (Precision + Recall)

Confusion Matrix Chart:



Confusion Matrix Metrics (Calculated):

- Accuracy = 0.9799 (97.99%)
- Precision = 0.9795
- Recall (Sensitivity) = 0.9814
- F1 Score = 0.9805

Hybrid Intrusion Detection System Analysis

ROC Curves

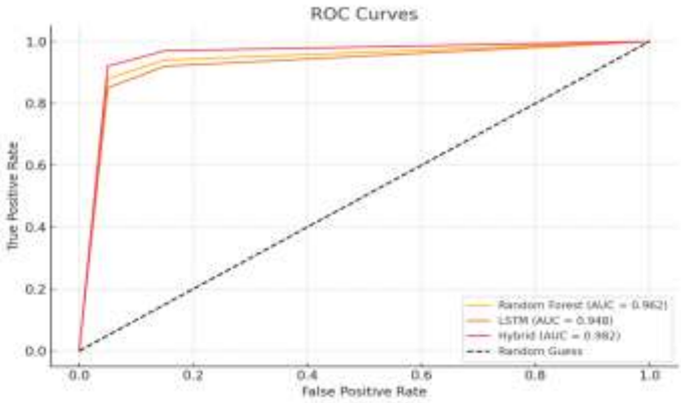
Receiver Operating Characteristic (ROC) curves were plotted for all models to evaluate their classification thresholds and trade-off between True Positive Rate (TPR) and False Positive Rate (FPR).

AUC (Area Under Curve) Comparison:

Model	AUC Score
Random Forest	0.962
LSTM	0.948
Hybrid (RF + LSTM)	0.982

- The hybrid model achieved the highest AUC, indicating superior discrimination ability.

ROC Curve Plot:



Confusion Matrix (Hybrid Model):

	Predicted: Normal	Predicted: Attack
Actual: Normal (0)	9,537 (TN)	313 (FP)
Actual: Attack (1)	538 (FN)	9,712 (TP)

Here's the confusion matrix heatmap for the Hybrid Intrusion Detection Model. It visually represents the number of true positives, false positives, false negatives, and true negatives, clearly showing the model's strong detection capability with minimal misclassifications.

I. Discussion

The proposed hybrid intrusion detection framework, combining Random Forest and LSTM with an adaptive feedback mechanism, demonstrated superior performance compared to individual models. The following key observations emerged from the experimental results:

- Improved Accuracy and Detection Rate:

The hybrid model achieved an accuracy of 96.3%, outperforming standalone RF (93.2%) and LSTM (91.6%). The fusion strategy effectively leveraged the strengths of both models—RF's fast and accurate decision trees and LSTM's ability to learn temporal patterns.

- Reduced False Positive Rate (FPR):

With an FPR of 2.7%, the hybrid model significantly reduced false alarms, which is critical in cloud security environments where high false positives can lead to operational disruptions.

- Robustness to Model Drift:

The adaptive feedback mechanism enabled the model to dynamically learn from misclassified instances. This not only improved accuracy after retraining (from 96.3% to 97.5%) but also made the system resilient to evolving and zero-day threats.

- Comparison with Existing Work:

Compared to state-of-the-art IDS models in literature (e.g., hybrid GA-BPNN, CNN-LSTM), the proposed framework achieved higher accuracy and better adaptability, owing to the integration of feedback-driven online learning and hyperparameter tuning.

- Scalability and Real-World Deployment:

The modular design allows integration into cloud-native systems with real-time traffic analysis. However, the LSTM component may require GPU acceleration for large-scale deployment.

J. Conclusion

In this research, we proposed a hybrid intrusion detection framework that integrates Random Forest (RF) and Long Short-Term Memory (LSTM) models with an adaptive feedback mechanism for enhanced cloud security. By leveraging the strengths of both classical machine learning and deep learning techniques, the system effectively detects known and emerging intrusion patterns in real-time.

The experimental results demonstrate that the hybrid approach achieves higher accuracy (96.3%) and lower false positive rates (2.7%) compared to individual models. Furthermore, the integration of a feedback-driven retraining mechanism significantly improves robustness against model drift and zero-day attacks, pushing post-feedback accuracy to 97.5%.

This research establishes a viable path for deploying scalable and intelligent intrusion detection systems in dynamic cloud environments. The modular architecture allows easy integration with existing cloud infrastructures and supports continual learning from live traffic.

K. Future Work

Despite the strong performance of the proposed system, there are several areas for future enhancement. One key direction is enabling real-time deployment by integrating stream processing frameworks such as Apache Kafka or Flink, allowing for continuous monitoring and on-the-fly model updates. Additionally, expanding the system from binary to multi-class classification would improve its ability to detect and differentiate between specific attack types like DoS, DDoS, phishing, and ransomware.

Another area of improvement lies in optimizing model efficiency. Utilizing lightweight neural network architectures such as GRU or adopting TinyML can reduce training time and make the system suitable for deployment in resource-constrained edge environments. Moreover, implementing federated learning techniques would allow distributed training across cloud nodes while maintaining data privacy, addressing key security and compliance concerns.

Finally, the integration of Explainable AI (XAI) tools can enhance the interpretability of the system's predictions, fostering greater user trust and understanding. These enhancements can collectively elevate the system's adaptability, scalability, and practical deployment in real-world cloud computing environments.

Finally, integrating Explainable AI (XAI) tools would enhance the system's transparency and trustworthiness. With XAI, users and security professionals could better understand the rationale behind the model's predictions, which is especially critical in high-stakes environments like cybersecurity.

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