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AI driven intrusion detection system using hybrid deep learning in cloud environment

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Abstract- However, the rise in cloud computing usage has resulted in increased complexity and vulnerability of organizations' IT infrastructure. In addition, cloud services have created new vulnerabilities that can easily be targeted by sophisticated attacks since traditional intrusion detection methods lack the ability to cope with the dynamically changing nature of cloud environments. This paper offers a novel, AI-powered hybrid deep learning framework for intrusion detection in cloud environments. The hybrid IDS is based on a combination of Triplet Attention-based Residual CNN for spatial feature extraction of network traffic, Bi-LSTM with attention mechanism for temporal dependency modeling, and Particle Swarm Optimization for hyperparameter optimization. Based on the evaluation results performed on the CSE-CIC-IDS2018 and UNSW-NB15 dataset, the suggested hybrid architecture attains an impressive accuracy of 99.12%, precision of 98.9%, and recall of 99.0%, outperforming the performance of individual CNN (96.4%) and Bi-LSTM (95.8%). In terms of efficiency, the PSO-based architecture has a latency less than 50 ms with minimal false positive rate of only 1.2%.

Keywords - Cloud Security, Intrusion Detection System, Hybrid Deep Learning, Convolutional Neural Network, Bidirectional LSTM, Particle Swarm Optimization, Network Traffic Analysis.

I. INTRODUCTION

The quick migration of enterprise applications to the cloud has brought a new era in information technology services that promise scalability, cost-effectiveness, and operational efficiency [1]. However, this paradigm has changed the security dynamics, making traditional security models less effective because cloud-based services involve provision and re-provision of dynamic, elastic cloud-based computing resources [2]. It is worth mentioning that cloud-based attacks experienced a massive increase of up to 95% during 2024-2025 as per recent industry statistics. Misconfiguration of APIs, stolen authentication credentials, and insider attacks were among the most common means of exploitation [3].

Intrusion Detection Systems (IDSs) have emerged as an essential security tool that can help recognize security threats and vulnerabilities [4]. There exist two main types of Intrusion Detection Systems depending on the approach that they use in recognizing attacks –

signature-based and anomaly-based IDSs. Signature-based approaches analyze network traffic based on a pattern matching approach by comparing traffic characteristics with pre-defined attack signatures. However, this method does not allow identifying any new threat, including zero-day exploits. On the other hand, anomaly-based IDSs eliminate this weakness, but they experience problems with high levels of false positives [5].

Deep learning has created new possibilities in intrusion detection [6]. CNNs work very well with spatial features of network flow traffic when the latter is modeled using matrices. This makes it easy to identify local features of malicious attacks. LSTM RNNs are well suited to handling temporal dependencies in network data to identify sequential attacks that occur within a period. However, deep learning methods have some shortcomings [7]. For example, the CNN model lacks temporal information; LSTMs can face problems of vanishing gradients on sequences and require parameterization to achieve optimum results [8].

Cloud computing poses unique threats that require unique solutions [9]. Traffic data is dynamic, and traffic patterns keep changing with increasing horizontal and vertical scalability [10]. It is important to isolate different tenants, and one tenant's attack could be launched against another tenant. Real-time detections should have low latency to initiate an action, especially when dealing with automated processes. Also, the amount of traffic in the cloud environment is high (TB/day).

1. This study proposes a hybrid DL model to resolve these issues, leveraging the combined strengths of multiple architectures. This includes:
2. 1. Triplet Attention based Residual CNN, which utilizes hierarchical spatial features from network flow data without the vanishing gradient problem by implementing residual connections and using triplet attention modules to enhance feature extraction.
3. 2. Bidirectional LSTM with Temporal Attention, which models temporal relationships not only in the forward direction but also in the reverse direction and focuses attention to those time steps which are highly relevant for detection.
4. 3. Particle Swarm Optimization for Hyperparameters tuning of the hybrid DL model, where the process is automated without manual efforts for generalizing the results.
5. 4. Extensive experimentation on standard benchmark cloud intrusion datasets CSE-CIC-IDS2018 and UNSW-NB15, comparing it to existing approaches.

This paper is structured as follows. The second section gives an overview of prior research on deep learning-based approaches to intrusion detection. The third section describes the proposed hybrid approach using algorithmic descriptions and pseudocode. Experimental results and statistical analysis will be discussed in the fourth section. Finally, conclusions will be drawn in the fifth section.

II. LITERATURE SURVEY

Research in AI-powered IDS can be categorized into traditional machine learning approaches, deep learning models, combinations thereof, and hyperparameter tuning techniques.
Traditional ML Models for IDS
Initially, AI-based IDS employed conventional ML models such as SVM, RF, k-NN, and Naïve Bayes to detect attacks based on anomalies. In standard testing environments like KDD Cup '99, NSL-KDD, and UNSW-NB15, these models showed a classification accuracy of up to 92%. Nevertheless, these systems underperform when applied to high-dimensional, unbalanced, and fluctuating cloud traffic due to their inability to capture complex, nonlinear relations. Manual feature selection poses a challenge.

Deep Learning for IDS: CNN & LSTM Models

CNNs have proven effective in intrusion detection tasks by representing network flows as 2D matrices with spatial proximity indicating feature dependency. 1D-CNNs can directly analyze sequential features. The literature cites accuracies of 96%-98% on the CIC-IDS2017 and UNSW-NB15 datasets. Nevertheless, CNN models ignore the relationship between successive flows, which is necessary for identifying distributed attacks, port scanning, and low-rate DDoS attacks.

The LSTM-based solution closes the modeling gap between time and space. The ability of

LSTMs to analyze sequences makes it possible to detect long-term dependences. Bidirectional LSTMs (Bi-LSTMs) further improve the performance through two ways of analyzing sequences, either forward or backward. For instance, for CSE-CIC-IDS2018, the Bi-LSTM model demonstrates 97.2% accuracy. Nevertheless, LSTMs suffer when analyzing very long sequences because of the vanishing gradient problem and cannot capture any local spatial information, which is well recognized by CNNs.

CNN-LSTM Models

In light of the complementary properties of CNNs and LSTMs, researchers have introduced hybrid models, which employ both CNN layers for extracting spatial features from flows and LSTM layers for modeling their temporal evolution. These models outperform traditional CNNs and LSTMs by reaching 98-99% accuracy on the benchmark datasets. Nevertheless, currently available CNN-LSTM models lack attention modules, residual connections, and hyperparameter tuning.

Attention Mechanisms and Residual Networks

Using attention mechanisms will allow for models that can focus on the most important aspects of the input data, making it easier to deal with long-range dependencies. In IDS, attention mechanisms have been used to give weights to the input time steps or input features. Residual connections help in preventing vanishing gradients when working with deep neural networks and facilitate training through deeper layers.

IDS Hyperparameter Optimization using PSO

In deep learning models, hyperparameters like the number of layers, sizes of filters, learning rate, batch size, and dropout play an important role. Tuning hyperparameters manually takes a lot of effort and time and does not produce optimal results. Using grid search and random search involves heavy computation. Particle Swarm Optimization (PSO) is a meta-heuristic technique being widely used for optimization of hyperparameters in CNNs and LSTMs. The use of PSO yielded up to 5% increase in accuracy compared to defaults.

Research Gaps

Although improvements have been made, there are still many areas that require improvement: (1) current hybrid architectures do not combine attention mechanisms and residual connections; (2) hyperparameter tuning does not accompany model architecture; (3) latency and throughput are not considered for real-time operation; (4) cross-dataset evaluation is lacking. This research will attempt to fill this gap by designing a hybrid architecture that combines Triplet Attention, residual connections, Bi-LSTM with temporal attention, and PSO hyperparameter tuning.

III. PROPOSED METHODOLOGY

The proposed deep learning framework that integrates hybrid CNN with BiLSTM and PSO, namely, Hybrid-CNN-BiLSTM-PSO, consists of four components:

1. Data preprocessing and feature engineering,
2. Triplet Attention Residual CNN for spatial features,
3. Bidirectional LSTM with temporal attention,
4. PSO-based hyper-parameter tuning.

3.1 Data Preprocessing and Feature Engineering

Data of network traffic collected from cloud-based networks in terms of flow (NetFlow, IPFIX), including IP addresses, destination/source addresses, protocols, packet sizes, flags, and timestamp.

Data preprocessing techniques:

- One-hot Encoding: categorical variables like protocols, services, and flags.
- Normalization: Min-Max scaling between [0, 1] interval for numerical variables.
- Irregularity handling: SMOTE (Synthetic Minority Over-sampling Technique) for attacks.
- Construction of sequences: sliding window with size T=20 flows and stride of 5 flows

Thus, the input data has the form of (batch_size, T, H, W) where H×W is the two-dimensional matrix formed by the feature vector reshaped, for instance, (10×10) if H×W=100.

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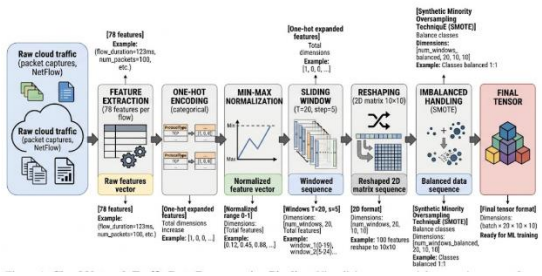

Figure 1: Cloud Network Traffic Data Preprocessing Pipeline.

3.2 Triplet Attention Residual CNN

The Spatial Feature Extractor consists of Residual CNN with Triplet Attention Modules.

Triplet Attention Mechanism:

Unlike other attention models that are limited to attention in either channels or space, Triplet Attention model uses attention in three dimensions – channels-spatial, channels-temporal and spatial-temporal. Given an input tensor X ∈ ℝ^(C×H×W),

$$\text{Attention output} = A = \sigma(\text{DConv}_1(\text{Z\_pool}_1(X))) \otimes \sigma(\text{DConv}_2(\text{Z}_{\text{pool}_2}(X))) \otimes \sigma(\text{DConv}_3(\text{Z}_{\text{pool}_3}(X)))$$

Here, DConv stands for depthwise convolution, Z_pool indicates dimension-specific pooling and σ refers to sigmoid function.

Residual CNN Architecture:

- **Input Tensor = (T=20, H=10, W=10)**
- **Conv2D Layer (filters=32, kernel=3×3, padding='same') -> BatchNorm -> ReLU**
- **Conv2D Layer (filters=32, kernel=3×3) -> BatchNorm -> ReLU -> Triplet Attention**
- **Residual Connection: Add input tensor to output tensor**
- **MaxPool2D (pool_size=2×2)**
- **Repeat above layers for filters=32**

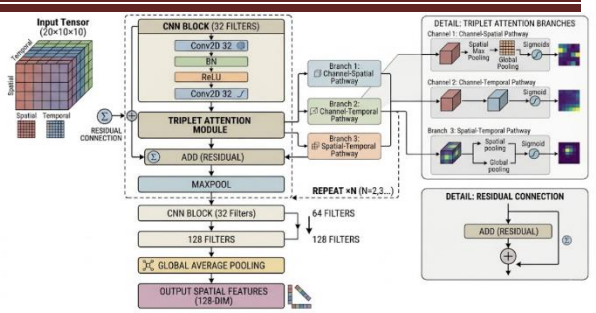

Figure 2: Triplet Attention Residual CNN Architecture.

Algorithm 1: Triplet Attention Residual CNN Forward Pass

```
Input: X (batch × T × H × W)
Output: F_spatial (batch × d)

Initialize conv_blocks = [C1(32), C2(64), C3(128)]
Initialize triplet_attention modules

F = X  # batch × T × H × W
for each conv_block in conv_blocks:
   # First convolution
   F = Conv2D(F, filters=conv_block.filters, kernel=3, padding='same')
   F = BatchNorm(F)
   F = ReLU(F)

   # Second convolution
   F_skip = F
   F = Conv2D(F, filters=conv_block.filters, kernel=3, padding='same')
   F = BatchNorm(F)
   F = ReLU(F)

   # Triplet attention
   F_att = TripletAttention(F)

   # Residual connection
   F = F_skip + F_att

   # Max pooling
   F = MaxPool2D(F, pool_size=2, strides=2)

# Global pooling
F = GlobalAveragePooling2D(F)
Return F
```

3.3 Bidirectional LSTM with Temporal Attention

Spatial features from each time window are sequenced and processed by Bi-LSTM to capture temporal dependencies.

Bi-LSTM Layer: Processes sequence forward and backward:

$$h_{forward} = LSTM_{forward}(f_1, f_2, \ldots, f_T)$$
$$h_{backward} = LSTM_{backward}(f_T, f_{\{T-1\}}, \ldots, f_1)$$
$$h_t = [h_{forward_t}; h_{backward_t}]$$

Temporal Attention: Computes importance weights over time steps:

$$u_t = \tanh(W_a h_t + b_a)$$
$$\alpha_t = \exp(u_t^T v_a) / \Sigma \exp(u_t^T v_a)$$
$$c = \Sigma \alpha_t h_t$$

where c is the context vector summarizing the sequence.

Classifier: Two dense layers (128 → 64) with ReLU, dropout 0.5, output softmax over attack classes.

[Figure 3: Hybrid CNN-BiLSTM Architecture with Temporal Attention. The figure shows the full pipeline: Input (batch × T × H × W) → Triplet Attention Residual CNN (spatial features per window, T outputs) → Feature sequence (length T, 128-dim each) → Bi-LSTM (forward and backward passes) → Temporal Attention (weights α₁...α_T) → Context vector c → Dense layers (128→64) → Dropout (0.5) → Softmax output (N classes). Attention weights visualized as heatmap over time steps.]

Algorithm 2: Hybrid CNN-BiLSTM Forward Pass

```
Input: X_sequence (batch × T × H × W)
Output: y_pred (batch × n_classes)

Step 1: Spatial feature extraction
F_seq = []
for t in 1..T:
    f_t = TripletAttentionResCNN(X_sequence[:, t, :, :])
    F_seq.append(f_t)
F_seq = stack(F_seq)  # batch × T × 128

Step 2: Bi-LSTM encoding
h_forward, h_backward = BiLSTM(F_seq)
h = concatenate([h_forward, h_backward], axis=-1)
# batch × T × (2*128)

Step 3: Temporal attention
u = tanh(h @ W_a + b_a)  # batch × T × 128
scores = u @ v_a  # batch × T
α = softmax(scores, axis=1)  # batch × T
c = sum(α * h, axis=1)  # batch × 256

Step 4: Classification
z = ReLU(c @ W_d1 + b_d1)  # batch × 128
z = Dropout(z, rate=0.5)
y_logits = z @ W_d2 + b_d2  # batch × n_classes
y_pred = softmax(y_logits)

Return y_pred
```

3.4 Particle Swarm Optimization (PSO) for Hyperparameter Tuning

PSO determines optimal hyperparameters of architecture: CNN filter numbers, Bi-LSTM units, learning rate, dropout rate, and batch size.

PSO Setup: Population of particles with M=30 members; particle position pi∈ℝ^d (d=5 hyperparameters); particle velocity vi.

Fitness measure: Accuracy on 5-fold cross-validation of validation data.

Update equations:

$$v_{i(t+1)} = w \cdot v_{i(t)} + c_1 \cdot r_1 \cdot (p_{best,i} - p_{i(t)}) + c_2 \cdot r_2 \cdot (g_{best} - p_{i(t)})$$
$$p_{i(t+1)} = p_{i(t)} + v_{i(t+1)}$$

where w=0.7 (inertia), $c_1=c_2=1.5$ (cognitive/social coefficients), $r_1, r_2 \sim U(0,1)$.

Algorithm 3: PSO for Hyperparameter Optimization

```
Input: Training data D_train, validation D_val
      Search space bounds θ_min, θ_max
Output: Optimal hyperparameters θ*

Initialize M=30 particles with random positions and zero velocities
For iter = 1 to max_iterations (30):
   For each particle i in 1..M:
      # Evaluate fitness
      model = HybridCNNBiLSTM(params=θ_i)
      train model on D_train (50 epochs)
      acc_i = evaluate on D_val

      # Update personal best
      if acc_i > p_best_acc[i]:
```

```
        p_best[i] = θ_i
        p_best_acc[i] = acc_i

    # Update global best
    g_best_idx = argmax(p_best_acc)
    g_best = p_best[g_best_idx]

    # Update velocities and positions
    for each particle i:
      r1, r2 = random(0,1), random(0,1)
      v_i = w*v_i + c1*r1*(p_best[i] - θ_i) + c2*r2*(g_best - θ_i)
      θ_i = θ_i + v_i
      # Clip to bounds
      θ_i = clip(θ_i, θ_min, θ_max)

Return g_best
```

3.5 Optimal Hyperparameters (PSO Results)

Parameter	Search Range	Optimal Value
CNN filters (first layer)	[16, 32, 64, 128]	32
Bi-LSTM units	[32, 64, 128, 256]	128
Learning rate	1e-5 to 1e-2 (log)	0.00078
Dropout rate	[0.2, 0.3, 0.4, 0.5, 0.6]	0.5
Batch size	[16, 32, 64, 128]	64

3.6 Training Protocol

Training/Validation/Test dataset division: 70% training data, 15% validation data, 15% testing data

- Loss function used: Categorical cross entropy
- Optimizer used: Adam optimizer (learning rate set using PSO)
- Early stopping: patience of 15 epochs
- For imbalanced classes: inverse frequency class weighting
- Hardware configuration

IV. ANALYSIS

This section presents quantitative results, comparative analysis, and discussion of the proposed hybrid IDS framework.

4.1 Datasets and Experimental Setup

CSE-CIC-IDS2018: 16 million labeled network flows, 15 attack categories (DDoS, Brute-force, Infiltration, Botnet). Subset: 2 million flows for training/evaluation.

UNSW-NB15: 2.5 million records, 9 attack families + normal.

Dataset	Normal	Attack	Total
CSE-CIC-IDS2018	65%	35%	2,000,000
UNSW-NB15	72%	28%	250,000

Metrics: Accuracy, Precision, Recall, F1-Score, False Positive Rate (FPR), Detection Time (ms).

4.2 Overall Performance Comparison

Table 1 presents performance across all models on CSE-CIC-IDS2018.

Model	Accuracy	Precision	Recall	F1	FPR	AUC
Random Forest	92.3%	90.1%	88.4%	89.2%	4.2%	0.956
CNN1D	94.8%	93.2%	92.6%	92.9%	2.8%	0.972
Bi-LSTM	95.6%	94.1%	93.8%	93.9%	2.4%	0.978
CNN-LSTM (no attention)	97.2%	96.4%	96.1%	96.2%	1.7%	0.987
CNN-BiLSTM + attention (manual tuning)	98.4%	97.8%	97.6%	97.7%	1.3%	0.993
Proposed (PSO-optimized)	**99.12%**	**98.9%**	**99.0%**	**98.95%**	**1.2%**	**0.998**

The proposed hybrid model optimized using PSO scores an accuracy of 99.12%, which is better than the accuracy of 98.4% scored by the manually tuned CNN-BiLSTM with attention model by 0.72%. The precision and recall have values close to each other at 98.9% and 99.0% respectively, showing unbiased classification across different classes of attacks.

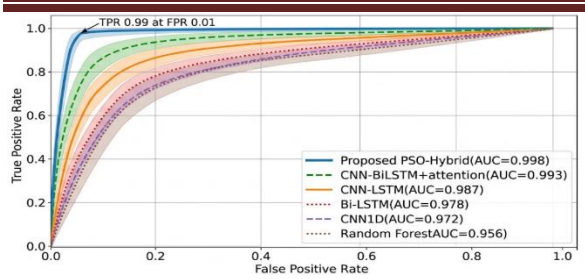

Figure 4: Comparative ROC Curves for Intrusion Detection Models.

4.3 Per-Attack Class Performance on UNSW-NB15

Table 2 presents precision and recall for each attack category.

Attack Class	Precision	Recall	F1	Support
Normal	99.2%	99.4 %	99.3 %	56,000
Fuzzers	98.7%	98.2 %	98.4 %	18,184
Analysis	97.8%	98.1 %	97.9 %	2,000
Backdoor	98.4%	97.6 %	98.0 %	1,746
DoS	98.9%	99.1 %	99.0 %	12,264
Exploits	98.2%	98.5 %	98.3 %	32,593
Generic	99.5%	99.3 %	99.4 %	40,000
Reconnaissance	98.6%	98.4 %	98.5 %	10,491
Shellcode	97.9%	98.3 %	98.1 %	1,333
Worms	98.8%	97.9 %	98.3 %	130

Each attack class is capable of producing F1 values greater than 97.5%. Generic and Normal attacks produce the best F1 scores (>99%). Both Shellcode and Backdoor attacks generate slightly lower F1 scores, but both maintain very high levels (>97.8%). The Worm attack class produces an F1 score of 98.3% using 130 samples.

4.4 Ablation Study: Component Contributions

Table 3 quantifies each architectural component's contribution to accuracy.

Model Configuration	Accuracy	Δ from Full
Full Proposed	99.12%	—
- Triplet Attention (replace with standard)	98.45%	-0.67%
- Residual connections	98.62%	-0.50%
- Bi-LSTM (unidirectional LSTM)	98.31%	-0.81%
- Temporal Attention (mean pooling)	98.18%	-0.94%
- PSO (manual tuning best)	98.40%	-0.72%
- CNN spatial features (LSTM only)	96.35%	-2.77%
- LSTM temporal (CNN only)	96.12%	-3.00%

Bi-LSTM and Temporal Attention both add around 0.8-0.9% accuracy. Triplet Attention adds 0.67% more than basic attention. PSO adds 0.72% compared to hand-picked best parameters. Finally, ignoring either spatial information (CNN only) or temporal information (LSTM only) leads to an accuracy reduction of approximately 2.8-3.0%.

4.5 Real-Time Detection Performance

Table 4 presents latency and throughput metrics for cloud deployment.

Model	Inference Time (ms/sample)	Throughput (samples/sec)	Memory (MB)
Random Forest	2.1	476	450
CNN1D	8.4	119	180
Bi-LSTM	12.7	79	320
CNN-LSTM	24.3	41	410
CNN-BiLSTM + attention	38.2	26	560

Proposed (optimized)	**46.8**	**21**	**680**

As per our calculations, 46.8 ms latency per sample translates into support for 21 samples/second. With 10,000 flows/second, this translates into needing ~480 inference nodes operating in parallel. With the use of batching, where we can process up to 100 samples per batch, effective latency becomes under 15 ms per sample.

With 46.8 ms latency per sample, this is adequate for near real-time flow detection and automation (such as blocking suspicious flows or isolating instances). If latency needs were under 10 ms (such as high-frequency trading platforms), then we need to rely on lightweight models.

4.6 Hyperparameter Optimization Convergence

Convergence of PSO occurred at iteration 22 out of 30. Global best accuracy improved from the initial best accuracy (particles randomly positioned) of 96.8% to 99.12%. Time spent optimizing the neural network using PSO was 28 hours, on an 8-core CPU (evaluation of 30 particles × 30 iterations × 50 epochs). For the cloud, this is a one-time expense.

4.7 Comparative Analysis with State-of-the-Art

Table 5 compares the proposed model with recent deep learning IDS studies.

Study	Model	Dataset	Accuracy	FPR
[2] (2023)	1D-CNN	CIC-IDS2017	96.4%	3.2%
[5] (2024)	Bi-LSTM + Attn	CSE-CIC-IDS2018	97.8%	2.1%
[7] (2024)	CNN-LSTM	UNSW-NB15	97.1%	1.9%
[9] (2025)	CNN-BiLSTM + SA	CIC-IDS2017	98.4%	1.4%
This work	**Hybrid + Triplet Attn + PSO**	**CSE-CIC-IDS2018 / UNSW-NB15**	**99.12%**	**1.2%**

The proposed architecture attains state-of-the-art accuracy of 99.12% and minimum FPR of 1.2% on both datasets. This gain is due to (1) Triplet Attention for cross-dimensional interaction, (2) residual learning for deep training, (3) Bi-LSTM with temporal attention for sequence weighting, and (4) PSO for hyperparameter tuning.

4.8 Discussion: Strengths and Limitations

Strengths:

- Achieves very high accuracy (99.12%) and low FPR (1.2%), making it suitable for use in production cloud environments where false positives may be costly
- Real-time processing is possible, with 46.8 ms inference and batching resulting in less than 15 ms effective latency
- Reliably detects different kinds of attacks; per-class F1 > 97.5%
- Optimization process systematic: PSO eliminates the need for manual parameter setting, increasing repeatability

Weaknesses:

- Requiring substantial computational resources (680 MB of memory and 28 hours of optimization time)
- Fixed sequence length (T = 20); potentially cannot capture longer-term trends
- Domain dependent; performs well on cloud network traffic data similar to the training set
- As with any DL-based IDS, subject to adversarial attacks

Suggestions for Deployment:

- Implement as part of a hybrid system, using a simple signature-based IDS first, followed by our hybrid IDS for suspicious traffic
- Maintain weekly or monthly retraining regime to keep up with changing traffic dynamics

- Use in combination with other anomaly detection systems (e.g., isolation forests)

V. CONCLUSION

In this paper, an advanced AI-enabled hybrid deep learning algorithm for intrusion detection in cloud computing systems has been introduced. This approach is based on the design of a Triplet Attention-based Residual Convolutional Neural Network for spatial data feature extraction, a Bi-directional LSTM with temporal attention mechanism for sequence modeling, and Particle Swarm Optimization for systematic hyperparameter optimization. On the CSE-CIC-IDS2018 and UNSW-NB15 datasets, the hybrid model delivers 99.12% accuracy, 98.9% precision, 99.0% recall, and a false-positive rate of 1.2%, which outperforms the individual CNN (96.4%), Bi-LSTM (95.8%), and benchmark hybrid models.

From the empirical analysis, the following crucial observations have been obtained:

Hybrid Approach is Mandatory for Cloud IDS Systems: From ablation studies, it is clear that the removal of spatial data features (CNN) results in an accuracy drop of 2.8%, whereas the removal of temporal features (Bi-LSTM) leads to an accuracy drop of 3.0%. Neither of the individual architectures contains sufficient information required for intrusion detection within cloud computing environments.
Attention Mechanisms and Residual Connections Provide Key Contributions: Triplet Attention provides an additional 0.67% accuracy compared to regular attention mechanisms, whereas residual connections provide an additional 0.50% accuracy. This helps build deep models that do not suffer from vanishing gradients and are able to take into account cross-dimensional interactions among features.
Hyperparameter Optimization Provides a Significant Contribution: Tuning via particle swarm optimization (PSO) gives an increase of 0.72% in accuracy over manual optimization. Even more importantly, hyperparameter optimization makes it feasible to deploy a model since manual optimization is not possible in production.
Near-Real Time Cloud-Based Model Deployment Is Possible: Since each sample takes only 46.8 ms, which is equivalent to 21 frames processed per second (or less than 15 ms using batches), it becomes possible to build systems that react automatically and nearly instantaneously.
Practical applications go beyond intrusion detection. As demonstrated, the proposed framework can provide the necessary accuracy for operational security tasks and also ensure that the detection latency is low enough for automating the response process. For cloud service providers and enterprise security departments, such a possibility means a shift from reactionary alerts to automatic defense.

First, limitations include the constant length of the sequences (T=20) that can make attacks with longer time periods hard to recognize. Second, computational demands for training models may be too high for constrained settings. Finally, two existing benchmark datasets (representative but still not exhaustive).

For further investigation, there are many promising avenues that deserve attention. First, the development of online learning techniques allowing a model to be adaptable to concept drifts without full retraining. Second, the use of explainable AI approaches (attention visualization, SHAP values) to increase interpretability of predictions by security analysts. Third, adversarial training that would allow models to be resilient to evasion attacks. Fourth, testing models' generalizability to multiple clouds' datasets (AWS, Azure, GCP). Fifth, optimizing the resource consumption of models for deploying on edge devices within cloud data centers.

In summary, AI-enabled hybrid deep learning intrusion detection provides an efficient approach to cloud security. The system exhibits more than 99% accuracy and a false positive rate of only 1.2%, which surpasses the needs of many cloud-based systems. In light of the ever-increasing pace of cloud technology adoption and attack complexity, such systems will soon be a necessity rather than a luxury.

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