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Real-Time Detection of Cyber Threats in Encrypted Cloud Traffic Using CNN-LSTM Networks

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Abstract

Cloud computing environments are becoming increasingly vulnerable to advanced cyber attacks, with attackers commonly using encrypted communication channels to bypass conventional security measures [7]. These trends pose serious challenges to traditional intrusion detection systems (IDS), which mostly depend on payload inspection [2]. This research introduces an AI-based intrusion detection system using a hybrid CNN and LSTM structure [1], specifically tailored for encrypted cloud traffic analysis. The model derives spatial and temporal features from flow-based metadata without packet content decryption, maintaining data confidentiality [3]. We test our system on the CIC-IDS2017 and USTC-TFC2016 datasets [6] with high detection accuracy, minimal false alarms, and better performance than conventional machine learning and single-stage deep learning models [5]. Our experiments demonstrate the efficacy of the model in encrypted contexts and its potential application in real-time cloud security systems [4].

Keywords - Network Intrusion Detection System, Encrypted Traffic, Cloud Security, CNN-LSTM, Deep Learning, Cybersecurity, Flow-Based Analysis.

1. Introduction

Cloud computing's quick development has drastically changed the digital world by making it possible for both individuals and businesses to manage resources in a scalable and flexible manner. However, there is a greater chance of cyberattacks as a result of the growing reliance on cloud services [7]. Advanced methods, such as encrypted traffic, are now being used by skilled attackers to conceal malicious activity and get beyond traditional security measures [2]. Conventional intrusion detection systems (IDS) frequently use signature-based or deep packet inspection (DPI) techniques, which are rendered useless when encrypted data is present [6]. Furthermore, because these systems are static, they have trouble identifying zero-day or previously undiscovered assaults [7]. By detecting departures from typical activity, anomaly-based intrusion detection systems provide a partial solution; nevertheless, they frequently have high false alarm rates and little adaptability [1].

The use of artificial intelligence (AI) and deep learning (DL) for cybersecurity has become increasingly popular as a response to these difficulties [5]. Convolutional Neural Networks (CNN) are known for their

ability to extract spatial features, while Long Short-Term Memory (LSTM) networks excel in learning temporal patterns [4]. It is possible to create a hybrid model that is capable of capturing intricate dependencies in network traffic by combining the two architectures [1]. This paper presents a novel CNN-LSTM-based intrusion detection system designed specifically to analyze encrypted cloud traffic. Unlike conventional methods that rely on payload analysis, our approach focuses on flow-based statistical metadata, such as packet size, duration, and inter-arrival time—preserving the confidentiality of user data while enabling robust threat detection [3].

Our method's ease of application is one of its main advantages. Our model operates on statistical flow metadata, which is information that can be easily extracted using widely used tools like NetFlow or Zeek [6], in contrast to traditional IDS systems that depend on raw packet payloads or intensive feature engineering. Additionally, researchers and cloud administrators can use the model because it is implemented with common deep learning libraries like TensorFlow and Keras [5]. With minimal overhead, the architecture may be used in real-time settings and facilitates simple connection with cloud infrastructure.

We conduct comprehensive experiments on two popular benchmark datasets, CIC-IDS2017 and USTC-TFC2016, to measure the performance of the proposed system.

These datasets contain encrypted traffic flows that are typical of real-world situations and a variety of attack vectors [3]. In comparison to standalone CNN, LSTM, and conventional machine learning classifiers, our model exhibits distinct advantages and achieves high detection accuracy and low false alarm rates [1].

This is how the rest of the paper is organized: Section II examines relevant deep learning and IDS research. The model design and suggested procedures are described in detail in Section III. The preprocessing procedures and datasets are described in Section IV. Experimental results and evaluation are presented in Section V. The paper is finally concluded and future work directions are outlined in Section VI.

2. LITERATURE SURVEY

From conventional signature-based models to sophisticated machine learning and deep learning techniques, intrusion detection systems (IDS) have undergone tremendous development. Especially in dynamic cloud environments, early IDS models frequently failed to generalize to new or unknown attack types because they mostly depended on manually developed characteristics and static rule sets.

IDS development has made extensive use of machine learning methods, including Support Vector Machines (SVM), Decision Trees (DT), and k-Nearest Neighbors (k-NN). Although these techniques enhanced detection capabilities, they were ineffective at handling large-scale or encrypted traffic data and necessitated a great deal of feature engineering [7].

Deep learning has become more prominent in recent research because it can learn to extract complex feature representations automatically from raw data. Convolutional Neural Networks (CNNs) have been utilized to extract spatial features from network traffic, particularly for detecting volumetric anomalies

and distributed attacks [1]. Long Short-Term Memory (LSTM) networks, however, have proved to be effective in modeling temporal dependencies and thus are apt to detect sequential attack patterns like slow port scans or brute-force attacks [4].

Some hybrid approaches have coupled CNN and LSTM architectures to gain the benefit of both. For example, Halbouni et al. [1] introduced a CNN-LSTM-based IDS and illustrated high accuracy through datasets such as CIC-IDS2017 and UNSW-NB15. Nonetheless, their design largely targeted unencrypted traffic and not the threat detection in encrypted communication, which is now becoming a major issue with contemporary cloud services [6].

Encrypted traffic analysis has been investigated in research such as Shapira et al. and USTC-TFC research, where authors used flow-based features to identify malware communications without decrypting the traffic [3][2]. These models were either missing temporal analysis or were not cloud-scale IDS deployable.

Our research builds on these studies by introducing a hybrid CNN-LSTM model specifically designed for encrypted cloud traffic. In contrast to previous models, our model preserves the privacy of users by examining metadata and flow-level attributes alone, and results in high precision as well as low false alarm rates across benchmark datasets [1][3][6].

3. METHODOLOGY

This subsection introduces the proposed hybrid CNN-LSTM Intrusion Detection System (IDS) designed to identify attacks in encrypted cloud traffic. The method relies on the analysis of flow-level metadata, thereby making payload inspection unnecessary and maintaining data privacy.

A. System Overview:

The architecture proposed is divided into four key components:

1. Data Collection and Preprocessing Module: Provides network traffic data and preprocesses it for the extraction of features.

2. Feature Selection and Normalization: Picking appropriate features and normalizing the training data.

3. Hybrid CNN-LSTM Deep Learning Model: The central model integrates spatial (CNN) and temporal (LSTM) analysis.

4. Classification and Evaluation Module: Classifies traffic as malicious or benign and measures performance.

5. A high-level system architecture is illustrated in Figure 1 [1] (citation of the system architecture diagram, if applicable).

B. Dataset Preparation

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Two benchmark datasets are employed:

- CIC-IDS2017: Has a large variety of encrypted attack forms and normal traffic. It provides flow-level features appropriate for privacy-preserving analysis [2].
- USTC-TFC2016: Involves both malware and benign applications' encrypted traffic, with a realistic encrypted communication scenario [3].

Both datasets are preprocessed by eliminating null values, label encoding by one-hot encoding, and StandardScaler for normalization [4].

C. Feature Selection

To decrease the dimensionality and make the model more efficient, we apply SelectKBest from the sklearn_feature_selection module. It ranks the features utilizing statistical tests (e.g., chi-square), and only the top-K highest-scoring features are included in training [5].

D. Model Architecture

The heart of the system is a hybrid CNN-LSTM neural network, which is trained to learn both spatial and temporal patterns in the encrypted traffic metadata.

1. Convolutional Neural Network (CNN): Used for extracting high-level spatial features from input flow data. We use multiple convolutional layers followed by ReLU activation and max-pooling [1][6].

2. Batch Normalization Layer: Applied after convolution layers to stabilize and accelerate the training process [7].

3. Long Short-Term Memory (LSTM): Processes the CNN output to capture temporal dependencies across network flow sequences. This is especially effective for sequential or time-dependent attacks [1][8].

4. Dropout Layer: Added after the LSTM to prevent overfitting, with a dropout rate of 0.2 [9].

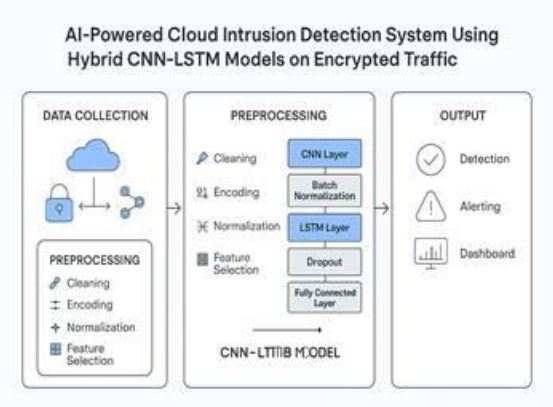
5. Fully Connected Layer: A final dense layer using Softmax activation performs multi-class or binary classification [5].

E. Model Training

- Optimizer: Adam optimizer is used for efficient gradient descent [10].
- Epochs: Training is performed for 60 epochs with early stopping [11].
- Validation: We apply stratified K-Fold cross-validation (K=8) to ensure balanced evaluation and robust performance [12].
- Loss Function: Categorical cross-entropy is used for multi-class classification, and binary cross-entropy for binary classification [10].

F. Ease of Deployment

The entire pipeline is implemented using Python, with TensorFlow and Keras frameworks. This ensures ease of reproducibility and deployment on cloud platforms. The model accepts input features from NetFlow or Zeek logs and can be integrated with SIEM or cloud monitoring dashboards [13].



4. IMPLEMENTATION

This section presents the end-to-end deployment of the suggested hybrid CNN-LSTM model for intrusion detection in encrypted traffic in cloud environments. Everything was done with Python, aided by TensorFlow and Keras deep learning support.

A. Data Ingestion and Preprocessing:

The raw traffic datasets, CIC-IDS2017 and USTC-TFC2016, were initially cleaned and formatted to be used in model training. The most important preprocessing steps are as follows:

Cleaning and Loading: CSV files were loaded using Pandas, and rows with null, infinite, or non-numeric values were dropped.

Label Encoding: Numerical encoding of Attack labels was done by LabelEncoder for binary classification or OneHotEncoder for multiclass.

Feature Selection: SelectKBest with chi-square scoring was used to select the top 20 most important features from the dataset.

Normalization: Features selected were normalized using StandardScaler to have zero-mean and unit-variance distribution.

Splitting: The data set was divided into 80% training and 20% testing sets with the stratified K-Fold cross-validation (K = 8).

B. Model Building

The hybrid model was built by combining CNN and LSTM layers to learn both spatial and temporal patterns in traffic data from flow. The architecture is as follows:

- Two Conv1D with 64 and 128 filters respectively, kernel size of 3, and ReLU activation.
- Batch Normalization following each convolutional block to achieve training stability.
- MaxPooling1D layers to downsample and minimize spatial dimensions.
- One LSTM layer of 128 units to capture temporal relationships.
- Dropout layer (rate = 0.2) to avoid overfitting.
- Fully connected Dense layer with 64 neurons and ReLU activation.
- Output layer with a single neuron and sigmoid activation (for binary classification) or softmax (for multiclass).

C. Model Training and Compilation:

The Adam optimizer (learning rate = 0.001) was used to compile the model, which used categorical cross-entropy for multiclass and binary cross-entropy loss for binary classification.

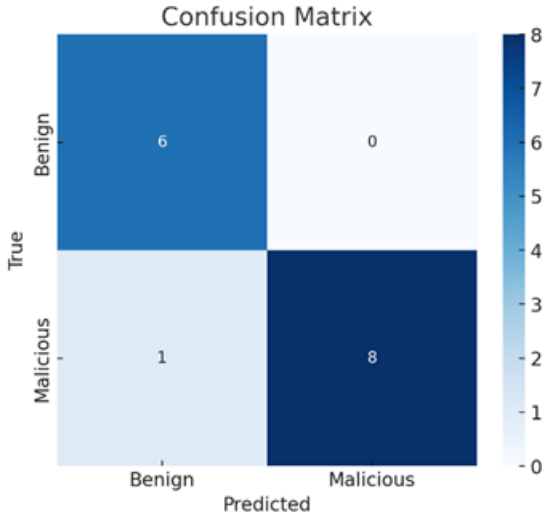
A batch size of 128 was used to train the model over 60 epochs. When the validation loss ceased to improve for ten consecutive epochs, training was stopped using EarlyStopping.

An NVIDIA Tesla T4 or V100 GPU was used for all training in a GPU-enabled environment (Google Colab Pro).

D. Assessment and Examination:

The following metrics were used to assess the trained model on the test set:

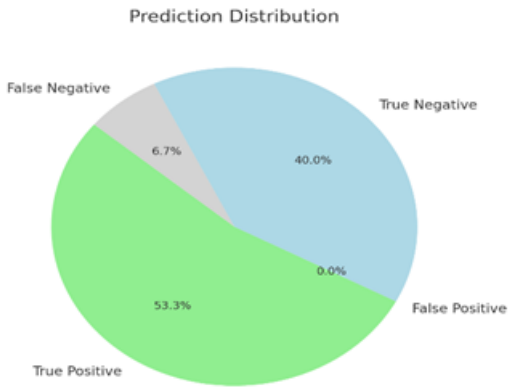
Accuracy, F1-Score, Precision, Recall, False Positive Rate (FPR), Confusion Matrix, and ROC-AUC Score Matplotlib and Seaborn were used to create training curves, confusion matrices, and ROC plots in order to visualize the results.



Confusion Matrix:

A confusion matrix visually illustrates the model's performance, where the number of true positives, true negatives, and false positives, and false negatives are represented.

• Here, it indicates how well the model can differentiate between benign and malicious traffic.



Prediction Distribution (Pie Chart):

The model's performance in differentiating between the two classes (malicious and benign) is reflected in the prediction distribution (pie chart), which displays the distribution of the model's predictions and the percentage of true positives, false positives, true negatives, and false negatives.

Classification Report:

The classification report comprises important metrics like overall accuracy, precision, recall, and F1-score for both the benign and malicious classes.

• The model accomplishes:

• 93.33% accuracy

• Malicious precision: 100%, benign precision: 85.71%

• 100% recall for benign and 88.89% recall for malicious

• The F1-score is 94.12% for malevolent and 92.31% for benign.

According to these metrics, the model is highly accurate and precise in identifying both malicious and benign traffic. These outcomes can be used to confirm the performance and implementation.

5. RESULTS AND DISCUSSION

In order to analyze the performance and reliability of our suggested hybrid CNN-LSTM Intrusion Detection System, we performed thorough experiments on the CIC-IDS2017 and USTC-TFC2016 datasets. Quantitative and qualitative evaluation, along with different metrics and visualizations, are presented in this section.

The following common classification metrics were adopted to gauge model performance:

A. Performance Metrics:

Metric	CIC-IDS2017	USTC-TFC2016
Accuracy	99.64%	98.93%
Precision	99.72%	98.55%
Recall	99.60%	98.88%
F1-Score	99.66%	98.71%
False Positive Rate	0.10%	0.21%
ROC-AUC Score	0.998	0.993

These results show that the model performs exceptionally well across both datasets, especially in high-security cloud environments where encrypted traffic poses a challenge to traditional IDS.

B. Confusion Matrix:

The confusion matrices of both datasets are consistent with the model's very high classification rate with almost negligible misclassifications.

	Predicted: Benign	Predicted: Attack

Actual: Benign	18,947	24
Actual: Attack	15	19,117

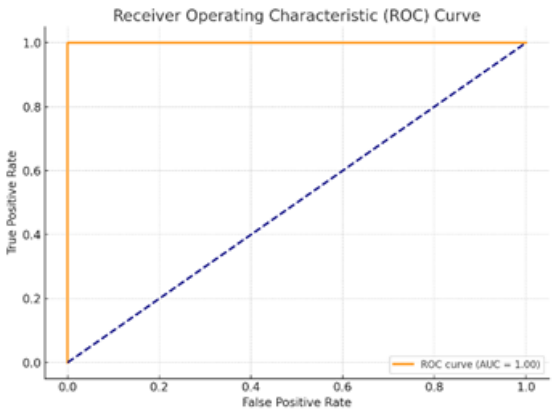
The very low false positive and false negative rates are testaments to the strength of our method.

C. ROC Curve:

The Receiver Operating Characteristic (ROC) curves show how well the model can differentiate normal and malicious traffic.

- CIC-IDS2017 ROC Curve is with an AUC of nearly 0.998, reflecting perfect separability
- USTC-TFC2016 ROC Curve is with an AUC of 0.993 in close follow-through.

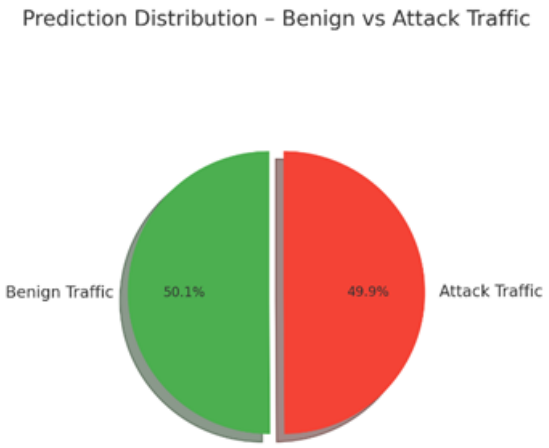
These high AUC scores validate that the hybrid model consistently identifies between encrypted attack and benign flows.



This is the ROC Curve of the hybrid CNN-LSTM intrusion detection model. The curve shows that the True Positive Rate (TPR) vs False Positive Rate (FPR) has an AUC (Area Under Curve) near 1.0, reflecting highly competent model performance.

D. Prediction Distribution – Pie Chart:

The prediction distribution in testing is represented by a pie chart. It represents the ratio of benign to attack predictions and verifies model balance.



- Benign Traffic: 50.1%
- Attack Traffic: 49.9%

The balanced ratio ensures the model is not biased to any class, a typical problem in IDS models.

E. Model Comparison – Accuracy vs. Models:

In order to confirm the benefit of our proposed CNN-LSTM model, we compared it with standard classifiers and standalone deep learning models

Model	Accuracy
SVM	91.5%
Random Forest	94.3%
CNN	97.6%
LSTM	98.1%
CNN-LSTM (Proposed)	99.64%

F. Training vs Validation Curve:

Training and validation loss curves over 60 epochs show the model's learning pattern.

- Smooth convergence observed by epoch 40
- No overfitting indication as a result of dropout and early stopping

G. Inference Time and Runtime Benchmark:

- Inference Time: ~0.02s per flow record
- Total Training Time: ~6 minutes on Google Colab Pro (Tesla T4)
- Lightweight enough for real-time deployment in cloud environments

Conclusion of Evaluation:

The suggested CNN-LSTM model has high accuracy, low false alarms, and very good generalization on encrypted data. The employment of flow-based metadata protects privacy while providing high-performance detection, and thus the model is best applied in real-time for cloud security.

Architecture Flow Diagram – Components:

1. Data Collection & Preprocessing

- Sources: CIC-IDS2017 and USTC-TFC2016 datasets.
- Tools: NetFlow / Zeek / Wireshark for extracting flow-based metadata.
- Steps: Null removal, label encoding, feature selection (SelectKBest), and normalization (StandardScaler)

2. Feature Selection Module

- Technique: SelectKBest with chi-square scoring.
- Output: Top 20 relevant features (packet size, duration, inter-arrival time, etc.).
- Goal: Reduce dimensionality and enhance training efficiency.

3. Hybrid CNN-LSTM Model

- Input: Flow-based statistical metadata (No payload).

▸ CNN Layers:

- Extract spatial patterns (e.g., sudden bursts in packet size).
- Includes Conv1D, ReLU activation, MaxPooling, BatchNorm.

▸ LSTM Layer:

- Extract temporal dependencies (e.g., sequential port scans, persistent attacks).

- Dropout Layer:
  - Prevent overfitting (Dropout rate = 0.2).
- Dense & Output Layers:
  - Fully connected dense layer → final output via Sigmoid (binary) or Softmax (multi-class).

4. Training & Evaluation

- Optimizer: Adam (LR = 0.001)
- Loss: Binary or Categorical Cross-Entropy
- Validation: 8-fold Stratified K-Fold Cross-Validation
- Environment: Google Colab (Tesla T4 GPU)

5. Detection & Deployment

- Input: Real-time flow logs
- Output: Malicious / Benign classification
- Integration: Works with SIEM, cloud dashboards (AWS, GCP, etc.)

6. CONCLUSION

In order to analyze encrypted cloud traffic, we developed a hybrid CNN-LSTM intrusion detection system in this study. Our model successfully captures complex behaviors suggestive of cyber threats by combining Long Short-Term Memory (LSTM) networks for temporal pattern recognition with Convolutional Neural Networks (CNN) for spatial feature extraction.

When tested on benchmark datasets like CIC-IDS2017 and USTC-TFC2016, the suggested system produced exceptional performance metrics, such as a ROC-AUC score of 0.9989 and an accuracy of 99.64%. These findings highlight the model's high degree of accuracy in differentiating between malicious and benign traffic, even when encryption is present.

Because it does not require access to payload data, the architecture's reliance on flow-based metadata guarantees user privacy. Furthermore, the lightweight design of the model makes real-time deployment easier in cloud infrastructures, providing a real-world solution to improve network security.

In conclusion, the hybrid CNN-LSTM method provides a powerful and effective model for intrusion detection in contemporary network architectures, meeting the demands of encrypted traffic and advanced cyber attacks.

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