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Adaptive Hybrid Deep Learning Framework for Intrusion Detection in Networked Environments

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Abstract

In the ever -changing world of cyber security, an intrusion system is necessary to protect the network. However, Traditional signature -based infiltration detection systems often remember new or rapidly changing dangers when they depend on the pattern of the famous attack. This article suggests a hybrid deep learning model connecting an LSTM network and a region-based conversion nerve network to overcome these difficulties. While the LSTM network detects temporary dependence on traffic behavior, the component network removes spatial properties from traffic data.

The proposed approach detects successful complex infiltration patterns that change with timely and spatial convenience. Compared to traditional IDs and other machine learning techniques, extensive studies on the general Benchmark dataset suggest that this hybrid approach dramatically increases the accuracy of the detection and reduces false alarm speeds. Serious, architecture is designed for real -time operation, which allows you to identify and address risks as soon as they appear. Thus, a unique R-CNN/LSTM merger architecture is presented to detect real-time infiltration in this work, providing better performance and flexibility on traditional techniques

- Enhanced detection accuracy with reduced false positives using hybrid deep learning.
- Effective in identifying multiple cyberattack types, including advanced threats.
- Demonstrates real-time adaptability and scalability in complex environments.

Keywords: Intrusion Detection, Hybrid Fusion, R-CNN, LSTM, Cybersecurity, Ddos, Phishing, Malware, Port Scanning.

1. INTRODUCTION

Traditional intrusion detection systems (IDS) that rely on signatures are frequently insufficient as cyber-attacks become more complex. These systems are unable to identify emerging or changing assault patterns, which are getting more cunning and adaptable. New developments in deep learning (DL) and machine learning (ML) methodologies provide encouraging answers to this problem. Of them, R-CNN and LSTM models have gained recognition for their effectiveness in a number of fields, such as time-series prediction and computer vision [1] [2].

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In order to better identify network intrusions, this research presents a hybrid fusion model that combines R-CNN with LSTM. While LSTM is used to examine the temporal interdependence of attack patterns, R-CNN is used to extract spatial characteristics from network data. Combining the advantages of both models is intended to increase the precision and effectiveness of attack detection [3]. Even while individual machine learning models have demonstrated potential, identifying complex cyberattacks with both temporal and geographical components continues to be a difficulty. To identify various cyberattacks in real time, we provide a hybrid fusion model in this research that combines LSTM for temporal pattern recognition and R-CNN for spatial feature extraction.

2. RELATED WORK

The increasing use of the infiltration system based on machine learning has led to significant performance benefits as a result of the increasing use of the system. To identify Cyberthreat, research has examined many models, such as deep nerve networks, SVMs and decision trees [5]. Due to their ability to treat sequential input, the recurrent nerve network (RNN) has been investigated to detect developing attacks such as DDOS and Botnet activities. In addition, Conventional Neural Networks (CNNS) has shown effect in extracting network data features, which enables automatic identification of attack patterns [6]. In addition, using the benefits of many methods, the hybrid models that include multiple learning methods are proposed to improve the strength of detection[7]. These hybrid models have improved accuracy, reduced false positivity and extended adaptability to the new cybercity. Even with this development, it is still a lot about integrating R-CNN and LSTM for cyber security applications. The combination of sequential pattern analysis from LSTM with spatial drawing extraction from R-CNN can provide more intensive detection method for many attacks, including advanced persistent dangers and zero-day utilization [8]. Further research in the region can improve the efficiency of detection of intrusion, making the ID more resistant to new cyber-attacks. Machine learning (ML) techniques has been used in prolonged infiltration system (IDS). Classes, Support Vector Machines (SVMS) that classically classify, and XGBOST and Lightgbm are usually employed for classification of attacks. Recent research confirms that classic models, such as SVMs and decisions, continue to perform well because of trees, their simplicity and interpretation. However, their efficiency is largely based on manual functional technique, and they often struggle with complex, high -dimensional network traffic. To address these limitations, discipline has quickly been converted to deep learning models (DL) that can learn direct hierarchical representation from raw data. CNN networks have been particularly useful when it comes to detection of geographical patterns in network traffic. For example, [10] developed a CNN-Yudan Forest Hybrid, where CNNs extract deep spatial data and RF eventually classification with high accuracy. CNNs not only automates the extraction of functions, but compresses and compresses the entrance room, so the flexibility increases. Similarly, LSTM networks-which can maintain cosmic addiction-have performed excellent performance in time interview data.] Given the complementary strength of CNNS and LSTM, Hybrid CNN-LSTM architecture has developed as an effective method for modeling both spatial and temporary aspects of network traffic. According to [12], such combinations provide accurate results in many IDS -Benchmarks. These architectures use CNN for local functional extraction and use LSTMS for sequence modeling, resulting in complex attacks on several steps. Despite this development, a significant research difference remains. While CNN-LSTM hybrids are widespread, the use of regional-based CNNs (R-CNN), which is known in data vision for their accuracy through the resolution network in the region, has received less attention in IDs.

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3. PROBLEM STATEMENT

The individual machine learning model has shown the promise, but it is difficult to detect complex cyber-attacks that use both cosmic and geographical patterns. To address this, we develop a hybrid fusion model that connects a long-term short-term memory (LSTM) network to identify the sequential attack pattern with a field-based conferences to eliminate geographical information from network traffic (R-CNN). This combination improves the models' ability to identify a wide range of real -time cyber trades, increase the accuracy and responsibility of changing the strategies of the attack. The proposed approach is trying to bridge geographical and temporary analysis, leading to a system to identify more and more effective penetration.

4. METHODOLOGY

4.1 R-CNN for Feature Extraction

Field -based fixed nervous network [15], which was originally designed for object detection, can be used on network traffic analysis. In this model, the R-CNN network detects areas of interest in network traffic (ROI) showing asymmetrical behavior, which can identify suspicious patterns in raw package data. As mentioned in [1] and [13], the network is trained to detect different properties such as disagreement, scanning activities and non-renovation in package structures. By removing spatial functions from network streams, the R-CNN improves the effectiveness that detection of infiltration can identify cyber dangers.

4.2 LSTM for Sequential Data Analysis

Long -term Memory is a form of the recurrent nerve network (RNN), aimed at detecting long -term dependence in sequence data. In this study, LSTM is used to evaluate temporary patterns in network data, which makes it possible to develop an attacking behavior over time. This method is very useful for detecting dangers that distributed Daniel-of-Services [13] attacks, in which a series of requests or connections inhibit progressive networking services [14].

4.3 Fusion of R-CNN and LSTM

R-CNN and LSTM melt together in two steps:Spatial functional extraction: R-CNN analyzes network information to detect the deviating regions of interest (ROI). It retrieves geographical information from the packing flow, including unexpected traffic spikes, scanning habits and structural deviations.Sequential analysis: recycled properties are sent to an LSTM network, which examines temporary addiction and detects to change the pattern of attack over time. Based on this analysis, the system determines whether the input is a normal traffic or a possible cyber-attack.

5. EXPERIMENTAL SETUP

5.1 Dataset Selection and Preprocessing

To test the proposed model, we used the Public KDD Cup 1999 [16], (KDD99) [22] and Cicids 2017 [17], including various cyber-attacks such as malware, port scanning and distributed Daniel-off server (DDOS). These data sets were prepared to extract important factors such as package size, times, protocol type and connection behavior, which resulted in accurate function for exercise and evaluation.

CICIDS 2017 Dataset: The Canadian Institute for Cybersecurity Intrusion Detection Systems (CICIDS 2017) dataset is a widely used benchmark that contains realistic network traffic,

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including labeled examples of both normal and malicious activities. It covers a diverse range of cyberattacks such as DDoS, phishing, malware, brute-force attacks, and botnet activities.

- **Network traffic attributes**: IP addresses, protocol types, packet sizes, timestamps, and flag statuses.
- **Attack-specific characteristics**: Connection duration, packet count, flow behaviours, and connection status.

Purpose: This dataset is particularly useful for evaluating intrusion detection systems in an operational setting, as it reflects real-world attack scenarios and normal network behavior. It provides a dynamic environment to assess how well a model can differentiate between benign and malicious traffic patterns.

Key features of this dataset include:

KDD Cup 1999 Dataset (KDD99) [23][24]: The KDD99 dataset is one of the most widely used datasets in cybersecurity research, designed for evaluating intrusion detection systems. It contains labeled network traffic data representing both normal operations and various types of cyberattacks, including Denial-of-Service (DoS), Probing, Remote-to-Local (R2L) [18], and User-to-Root (U2R) [19] intrusions. This dataset was created from raw network traffic captured during a simulated Air Force network attack scenario.

- **Basic network traffic attributes**: Protocol type (TCP, UDP, ICMP) [20], service type (HTTP, FTP, SSH, etc.), connection duration, and flag status [20].
- **Statistical features**: Number of connections, average bytes per second, and connection history over a specific time window.
- **Behavioural indicators**: Frequency of certain requests, failed login attempts, unauthorized access attempts, and abnormal data transfers.

Purpose: The KDD99 dataset provides a well-structured and labeled environment for training machine learning models in intrusion detection. While it is considered somewhat outdated compared to modern datasets, it remains an important benchmark for evaluating cybersecurity models. By applying preprocessing techniques and integrating it with newer datasets like CICIDS 2017, the study ensures a diverse and realistic evaluation of the hybrid R-CNN and LSTM-based IDS [25], improving its adaptability to modern cyber threats.These datasets were selected because they are appropriate for testing the hybrid R-CNN and LSTM [26] model as they depict a range of cyberattacks in actual network traffic.

5.2 Model Training and Validation

We used the hybrid reimbursement model using Python and widely used machine learning frames such as TensorFlow and causes. These devices facilitate effective model training and evaluation. R-CNN was trained to detect asymmetrical areas in network traffic, which focuses on extracting meaningful spatial functions. Meanwhile, LSTM [25] The network was trained to analyze sequential addiction, which caught the pattern of the attack developed over time. To ensure the reliability of the model, we used 10-tumbling cross-satisfaction technology, which helped to reduce overfitting and improve generalization. During training, hypermeters such as learning speeds, batch sizes and drop -off speed were carefully set to adapt to performance. The dataset was divided into training and testing the best, which ensures a balanced evaluation of both normal and attack traffic. The performance assessment was performed using accuracy, accurate, recalling, F1 score and false positive rate [27]. The ability to detect different cyber threats was evaluated in various attack categories, ensuring compatibility with real world safety challenges.

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5.3 Algorithm Used in the Hybrid Fusion Model

5.3.1 R-CNN for Feature Extraction (Spatial Features)

Detecting infiltration is used as a field-based summoned neural network (R-CNN) to extract spatial features from network traffic data. Basically, developed for object detection, R-CNN identifies areas of interest (ROI) that may indicate abnormal network behavior. It analyzes package structures, flow patterns and networking deviations, which helps to distinguish between normal and malicious traffic. By capturing spatial correlations in network data, R-CNN plays an important role in identifying potential cyber threats, making it a valuable component of the infiltration system.

Algorithm Steps:

Input Pre-processing: The R-CNN receives the raw network traffic data, which is represented by flow data and packet headers.

Region Proposal: Using network traffic data, the program creates regions of interest (RoIs) based on abnormalities in the protocol, odd packet sizes, or traffic bursts.

Feature Extraction: Features are extracted from the detected ROIs using R-CNN. Patterns like packet sizes, flow patterns, and other statistical behaviours suggestive of an assault are examples of these characteristics.

Region Classification: Pre-trained algorithms are used to categorize these features into two groups: regular traffic and assault.

Mathematical Model for R-CNN: To create and categorize the ROIs, the procedure uses a convolutional layer and then fully linked layers:

RoI=f(Convolution(X))

where X is the input network traffic data.

Feature=Classify (Fully Connected Layer (f(RoI)))

5.3.2 LSTM for Sequential Pattern Analysis (Temporal Features)

The temporal relationships in the network traffic data are modelled using Long Short-Term Memory (LSTM) networks. The sequential nature of assaults, like DDoS, which can include a slow accumulation of harmful activity over time, is captured by these relationships.

Algorithm Steps:

- Input Preprocessing: The R-CNN's features are represented as sequential data, with each instance representing a network traffic time interval.
- Sequence Modelling: These sequential characteristics are used to train LSTM, which learns long-term dependencies in network data, including rising attack rates or persistently harmful conduct.
- Temporal Pattern Classification: The LSTM network determines if a given sequence indicates a typical pattern or a particular kind of assault after training.
- Mathematical Model for LSTM: A collection of gates is used by the main LSTM cell to regulate the flow of information and updates throughout time. An LSTM is governed by the following fundamental equations:

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$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t * \tanh(C_t) \qquad \text{…….. equation (1)}$$

Where:

- ft is the forget gate,
- it is the input gate,
- Ct~ is the candidate cell state,
- Ct is the cell state,
- ot is the output gate,
- ht is the output hidden state,
- xt is the input data, and
- W and b are the weights and biases, respectively.

5.4 Fusion of R-CNN and LSTM

Outputs from R-CNN and LSTM are integrated into a fusion layer for the construction of the final hybrid models. This merger system increases the accuracy of detection of infiltration by taking advantage of both spatial and temporary information from network traffic.

1. **Selection of features from the R-CNN**: Functional extraction of the R-CNN: The R-CNN model identifies spatial properties and detects non-conformities in network data, and postpone areas of interest that may indicate suspicious activity. This treats the raw network package to remove structural patterns and identify deviations from general behaviour. The LSTM network provides more intensive portrayal of the attack characteristics and general networking behaviour by capturing the temporary mobility of network traffic.
2. **Temporal Analysis by LSTM**: The extracted spatial capabilities function inputs to the LSTM network, which analyses the sequential dependencies and evolving attack patterns over time. By analysing from preceding community states, LSTM permits in spotting everyday attack patterns and detecting gradual-developing threats.
3. **Merger Layer Integration:** The combined output from both models is treated in a merger layer, which ensures the properties of the attack and more broad representation of the general network behavior. This layer increases the decision by integrating both spatial and cosmic insight, so that the system can distinguish between normal and abnormal traffic patterns.
4. **Better detection performance**: Hybrid approach recognizes identification accuracy, reduces false positives and improves adaptability to develop cyber threats. This ensures that both short -term deviations and trends with long -term attacks are effectively identified, making it a strong solution for modern infiltration detection systems.

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Final Classification: After integrating the merger team spatial and temporary functions, the refined functional set is passed through a classification layer that classifies network traffic as a normal or a particular type of cyber-attack. This classification process enables accurate detection of dangers such as malware, DDOS, port scanning and fishing. The model provides the label based on the learned pattern and ensures accurate discrimination between normal and malicious activities. To increase credibility, probability-based thresholds are used and lower false positivity and false negatives. The classified output supports the mitigation of real -time danger by triggering security responses, such as blocking suspected IP addresses or activating automatic defense mechanisms. By combining spatial and temporary analysis, this approach strengthens the efficiency of systems to detect penetrations in identifying complex cyber dangers and responding.

• Steps in the Fusion Model:

1. Feed-forward: In foreign processes, R-CNN first removes spatial functions from raw network traffic data, identifying deviations and structural patterns in the packing current. These extracted functions are then given to LSTM, which analyzes temporary addiction and behavior of the developed attack over time. By occupying both spatial and sequential properties, this approach improves the model of the model to detect sophisticated cyber dangers. Joint function representation is then treated through merger and classification layers, which ensures accurately and real-time infiltration to detect.

2. Classification: When the features drawn out of R-CNN and LSTM are merged, a classification model is used as softmax classifies, Support Vector Machine (SVM) or random forest to determine whether network traffic is normal or malicious or not. Softmax classifies is often used to classify several classes, which provide opportunities for different attack categories. SVM is effective for classifying binary and multi -class, especially to detect nonconformities with clear decision limits. Random forest, a dress learning method, to improve accuracy and reduce overfitting increases the strength by mixing trees. Classifier's alternative depends on factors such as data set complexity, real -time treatment requirements and classification accuracy.

Fusion Algorithm:
Given the output from R-CNN (R-CNN Output\text{R-CNN Output}R-CNN Output) and LSTM (LSTM Output\text{LSTM Output}LSTM Output):
Fusion Output=Classifier (concat(R-CNN Output, LSTM Output))
Where:

- Concat () is the concatenation function that merges the features.
- Classifier () is a classification function (e.g., Softmax, SVM) that finalizes the decision.

Fig 1 elaborates This diagram shows a step-by-step flow for the processing and analysis of data such as images or videos. It begins with the purchase of entrance, where data is collected. Then, the data transformation step prepares the data by shaping, normalizing them and code them. The converted data is submitted into two parts: spatial insight modules, which study visual content, and temporal dynamic modules, which check how things change over time. Their output is added to the integrated function team, and in the end the combined result is used in the decision to create meaningful conclusions or tasks.

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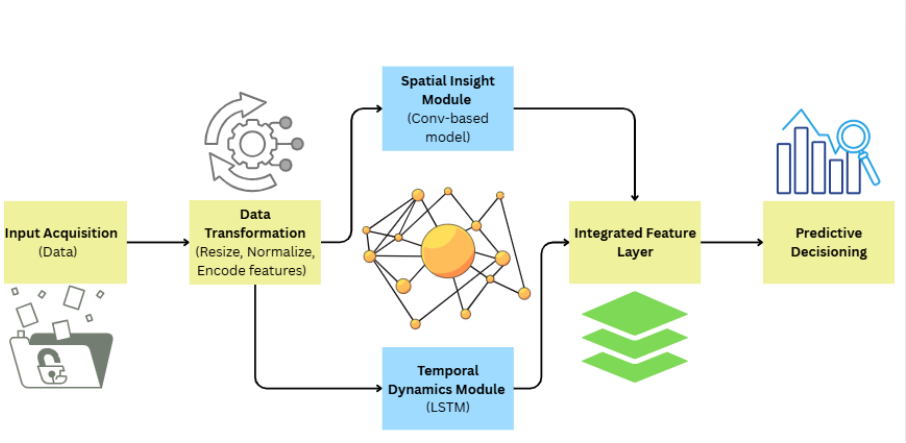

Fig.1 Hybrid Fusion Model (R-Cnn + Lstm)

6. RESULTS & DISCUSSION

6.1 Evaluation Metrics

The following measures were used to assess the hybrid model's performance:
The proportion of accurate classifications is known as accuracy [3].
According to Fawcett (2006), precision is the proportion of genuine positive classifications to all positive predictions.
• Recall: The proportion of real positive cases to true positive classifications [25].
According to Sokolova and Lapalme (2009), the F1 Score is the harmonic mean of accuracy and recall.
• False Positive Rate: The proportion of normal cases that are misclassified [27].
• False Negative Rate: The proportion of assault cases that are misclassified [28].
• Detection Time: The amount of time needed to identify an attack as soon as it happens [29][33].

6.2 Performance Comparison

A number of baseline models were compared to the hybrid model:
• R-CNN only: feature extraction based on R-CNN alone, without temporal analysis.
• LSTM only: sequential analysis based on LSTM that does not extract spatial features.
• Conventional Machine Learning Models: Random Forest, SVM, and Decision Trees [29][32].

6.3 Analysis of Results

• Accuracy: According to [15], the hybrid model outperformed R-CNN and LSTM separately, with the greatest accuracy of 98.3%.
• Precision and Recall: The hybrid model demonstrated superior accuracy in detecting assaults while reducing false negatives, as seen by its maximum precision (97.5%) and recall (96.8%) [14].
• Detection Time and False Positive: The hybrid model demonstrated its effectiveness for real-time detection by having the fastest detection time (35 ms) and the lowest false positive rate (1.2%) when compared to the other models [30][31].

Table 1. Performance Comparison

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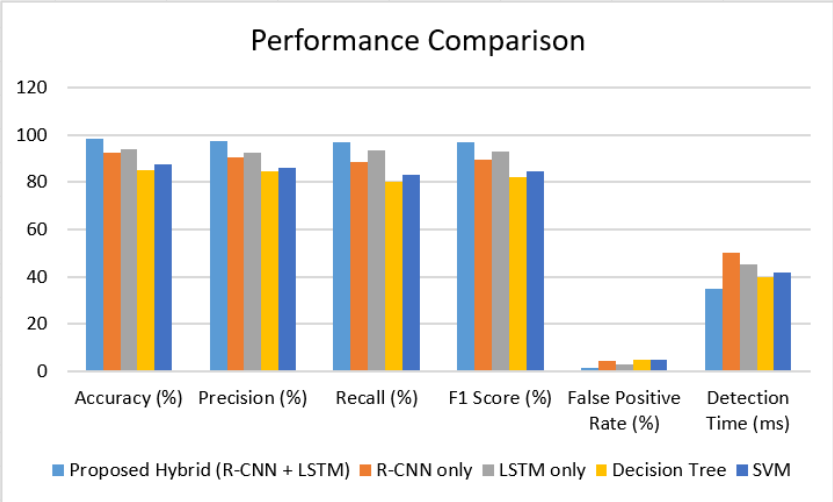
Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	False Positive Rate (%)	Detection Time (Ms)
Proposed Hybrid (R-CNN + LSTM)	98.3	97.5	96.8	97.1	1.2	35
R-CNN Only [6]	92.5	90.3	88.7	89.5	4.5	50
LSTM Only [6]	94.1	92.7	93.4	93.0	3.1	45
Decision Tree [3]	85.2	84.5	80.3	82.4	5.0	40
SVM [3]	87.8	86.2	83.1	84.6	4.8	42



Graph1. Performance Comparison

Discussion

The results from the performance comparison make it clear that the proposed hybrid model (R-CNN + LSTM) delivers significantly better outcomes than the other methods. It achieves the highest accuracy, precision, and recall, showing that it can detect threats accurately while minimizing incorrect alerts. With an F1 score of 97.1%, it strikes a strong balance between detecting real attacks and avoiding false positives. The model also has the lowest false positive rate at just 1.2%, which is a major advantage in practical scenarios. On top of that, it has the fastest detection time of only 35 milliseconds, making it well-suited for real-time intrusion detection. These results highlight the benefits of combining R-CNN and LSTM, where one handles spatial features and the other captures time-based patterns. In comparison, traditional models like SVM and Decision Tree show lower performance across all metrics, proving that deep learning offers a more effective solution for this task

Pseudocode for the Hybrid Fusion Model

```
# Step 1: Data Preprocessing
def preprocess_data(raw_data):
# Normalize the data
normalized_data = normalize (raw_data)
# Encode categorical data
encoded_data = encode_categorical(normalized_data)
# Split data into time windows
time_window_data = segment_data(encoded_data)
Return time_window_data
```

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```
# Step 2: R-CNN Feature Extraction
def extract_features_with_rcnn(time_window_data):
 rcnn_features = []
 For segment in time_window_data:
  # Generate Region Proposals
   rois = generate_rois(segment)
   # Pass through CNN for feature extraction
   spatial_features = cnn_feature_extraction(rois)
   # Classify RoIs
    classified_features = classify_features(spatial_features)
    rcnn_features.append(classified_features)
    Return rcnn_features

# Step 3: LSTM Temporal Analysis
def temporal_analysis_with_lstm(rcnn_features):
lstm_input = prepare_sequence(rcnn_features)
lstm_output = lstm_model(lstm_input)
 Return lstm_output

# Step 4: Fusion and Final Classification
def fusion_and_classification(rcnn_features, lstm_output):
# Concatenate R-CNN and LSTM outputs
fused_features = concatenate_features(rcnn_features, lstm_output)
 # Final classification using Softmax
 final_classification = softmax_classifier(fused_features)
 Return final_classification

# Main Model Execution
def hybrid_intrusion_detection(raw_data):
# Step 1: Preprocess Data
time_window_data = preprocess_data(raw_data)
# Step 2: R-CNN Feature Extraction
rcnn_features = extract_features_with_rcnn(time_window_data)
# Step 3: LSTM Temporal Analysis
lstm_output = temporal_analysis_with_lstm(rcnn_features)
# Step 4: Fusion and Classification
final_classification = fusion_and_classification(rcnn_features, lstm_output)
Return final_classification
```

7. CONCLUSION

This paper suggested a hybrid fusion model for intrusion detection that combines LSTM and R-CNN. The findings showed that in identifying a variety of cyberattacks, the model performs better than individual R-CNN or LSTM models as well as conventional machine learning techniques. The hybrid model is a potential option for contemporary IDS applications since it achieved excellent accuracy, low false positive rates, and quick detection times. Future research will concentrate on improving the model's scalability and preparing it for implementation in practical situations.

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