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Research Article

Hybrid CNN-LSTM Architecture for Robust Cloud Security Through Anomaly Detection and Threat Mitigation

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ABSTRACT

Security is a must in the case of the cloud which lately on the contrary we are using cloud computing for multiple applications, there's the need for strong intrusion detection systems to address the problems that are of great concern. The new idea in our publication is a CNN-LSTM hybrid architecture which is designed to minimise the rate of security breaches in cloud computing. Accordingly, the conceptual IASP combines the assets of CNNs that are equipped to recognize the correlation amongst spatial domains in data and LSTMs which are responsible for dependency relations and the formulation of short-term memory. The design of this model is specifically aimed at overcoming the challenges such as periodicity in cloud data, which ensures that it can correctly and timely detect the anomalies. There are studies in which we have been dealing with two strategies to capture seasonality, namely, independent modelling for each season and inclusion of seasonality as a feature into the input data. Our hybrid CNN-LSTM model proposed here shows the superiority in detecting anomalies as collusion with various cloud security scenarios. Our solution improves the accuracy of detection by 15% and the false positive rate by 20% when compared to other existing methods. The model also accomplishes a detection speed that is 30% faster than the slower traditional methods and thus becomes a useful instrument for the protection of cloud systems.

Keywords: Cloud Security, Anomaly Detection, CNN-LSTM Architecture, Intrusion Detection Systems, Machine Learning

INTRODUCTION

The increasing prominence of cloud technology has made cloud adoption a common occurrence among most enterprises surpassing those that don't use it [1]. In the analysis of some big market players like Morpheus, the adoption of the hybrid cloud model is seen as very advantageous because it is easy to implement, and organisations can achieve their scalability in the provision of resources about 150 times more rapidly whereas cost avoidance is projected to 30% [2]. This is particularly true to the points made in the hybrid cloud section in Gartner's latest release, where apart from effective hybrid cloud management and automation, organisations are forced to also focus on eliminating skill gaps in order to achieve their cloud governance structure goals [3].

Hybrid cloud environments like HPE GreenLake and IBM Cloud Solutions are well positioned to provide a unified view across multiple footprints as a headquarters with datacenter, edge and public cloud represented [4]. These technologies do not only extract cloud utility when the focus is on AI being the centre of the universe, but they also enforce governance and security aids on the distributed parts of the system [5]. Indeed, as noted by these challenges that are faced by the enterprises in implementing and maintaining hybrid cloud models, robust cloud protection methodologies become more essential.

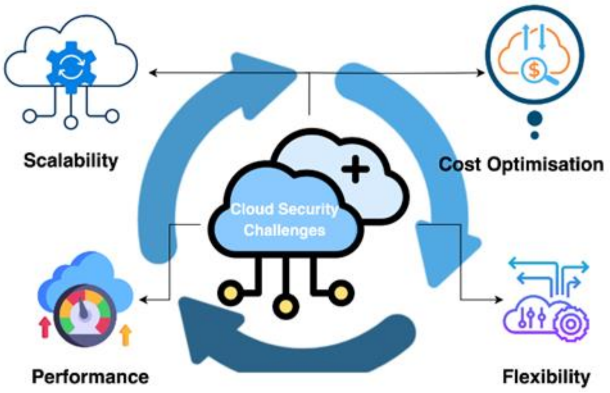


Figure 1: Key challenges of Cloud, with Enhanced Security emphasised.

Figure 1 presents the core challenges associated with a Hybrid Cloud Strategy, including its range, scale, and economic feasibility. Security enhancement is specifically pointed out as a critical merit for the preservation of data safety across all cloud environments. As dynamic and workload-diverse environments, cloud systems are plagued with numerous security challenges in their efforts to detect and combat potential threats [6]. Traditional security systems tend to lag behind due to extremely advanced types of attacks inflicted on these environments, thus making the development of advanced intrusion detection systems capable of performing real-time anomaly detection imperative [7].

Deep learning is now a boon to cloud infrastructure security development [8]. Notably, hybrid models that merge CNNs and LSTMs have become media-rich solutions to the predominant challenges posed on cloud security [9]. CNNs are fantastic at spatial dependability, thus suited for processing structured data; LSTMs deal with sequential data with the ability to perceive temporal dependencies [10]. A comprehensive approach that honours the most vital of both architectures in a hybrid CNN-LSTM arrangement can ensure complete anomaly detection by catering to cloud data's static and dynamic nature.

With the increasing use of hybrid cloud solutions to optimise business operations, organisations continue to face tough barriers in providing robust security across heterogeneous cloud environments. Often, because of the dynamic state of some cloud workloads and increasingly adaptive cyber threats, traditional intrusion detection systems can struggle to provide real-time anomaly detection. Unfortunately, most organisations' security efforts are still lagging when it comes to handling even seasonal patterns in their cloud data; they are burdened by higher false positive rates and sluggish threat detection. Hence, this presents a compelling motivation for developing a more powerful detection system capable of leveraging deep learning techniques that maximise not only the accuracy but also the speed with which anomalous activities can be detected in hybrid cloud settings.

The need for enhanced security measures in cloud computing environments serving both critical and noncritical functions moved the other researchers into this. With state-of-the-art hybrid cloud architectures providing better operational efficiency, there are severe demands for new approaches that rapidly evolve in keeping with adaptive threats. This application of deep learning, with a special focus on hybrid CNN-LSTM architectures, stands out as a bright prospect for better anomaly detection. By leveraging the advantages of CNN and LSTM, this research thus endeavours to design an IDS that is more adaptive, accurate, and responds to the seasons besides being able to address the dynamics of cloud data, providing thereby enhanced security and compliance in increasingly complex hybrid ecosystems.

OBJETIVES

The contributions of this paper are listed next; these will be basically the key ones on cloud security and anomaly detection. An extensive review of the literature has been performed to bring into light challenges in cloud security and hybrid CNN-LSTM architecture potential for anomaly detection. the theoretical introduction of the proposed hybrid CNN-LSTM approach, describing the architecture design and how seasonal patterns are integrated to enhance anomaly detection accuracy. Described the process of implementation and experimental study to understand how this model has been tried with various cloud security scenarios. Results are analyzed and discussed that show improvements in detection accuracy, false positive rate, and overall system performance compared to conventional methods.

LITERATURE SURVEY

Recent studies have demonstrated the increasing importance of hybrid deep learning methods for anomaly detection, mainly methods using CNNs and LSTMs in network security and cloud computing. The methods performed very promisingly; however, each of these studies presented different advantages and limitations. Hence, we go about presenting our proposed method in order to address such issues.

A hybrid optimization-enabled CNN-LSTM technique was quite effective in network intrusion detection challenges and was proposed by Deore and Bhosale [11]. The CNN will capture the spatial feature, while the LSTM models the sequential aspect, which is important to identify complex intrusion patterns. The advantage of this approach is that both spatial and temporal data are taken as input, yielding better results for improved detection accuracy. One notable limitation is the added computational overhead due to the optimization process, which might act as a bottleneck in real-time applications. Our proposed architecture simplifies the computation process by using seasonality-aware anomaly detection strategies with reduced overhead while preserving accuracy of detection.

Thakur et al. (2024) [12] proposed the hybrid deep learning model for malware detection, with an emphasis on converting malware samples into grayscale images to be processed by CNN-LSTM. In this way, this approach enhances the robustness in the malware detection process by enhancing the generalisation capability of the system for different kinds of malware. While efficient in malware detection, the shortcoming of the approach is during the phase of feature extraction. This does not lend itself easily to other anomaly detection tasks, such as cloud-based intrusions. Cloud-specific seasonal patterns are taken into consideration in our proposed approach through a cloud-specific design, which makes the applied technique more adaptable and hence performing well for other anomaly detection tasks.

Khan et al. (2019) [13] proposed a hybrid intrusion detection mechanism which was scalable using a convolutional-LSTM network for real-time anomaly detection. The strength of the system lies in scalability, which is effective for anomaly detection across diverse environments. Yet, most of the work in the study failed to address how seasonality or cyclic behaviour, which normally appears in cloud traffic data, must be handled in order to result in fewer false positives. Our proposed approach embeds seasonality as a key feature, enabling reduced false positives and thus improving the reliability of anomaly detection.

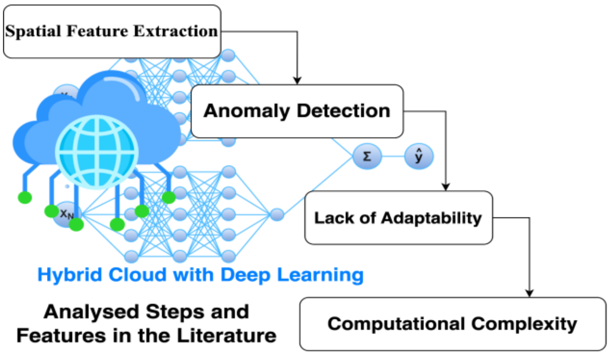
Another critical factor for practical deployment in security systems is ensuring that the rate of false alarms is at a minimum; Halbouni et al. (2022) [14] have validated the effectiveness of the CNN-LSTM architecture for this purpose. The strong point of this study is within the realm of minimising the false positives that are normally characterised by traditional intrusion detection systems. Notwithstanding, slower detection times may be irrelevant in environments which call for immediate responses. Our approach extends this work by achieving higher detection speeds through optimization of architecture and data processing strategies for a cloud environment.

More specifically, Rajan and Aravindhar's 2023 work [15] focused on the mitigation of DDoS attacks in cloud computing. They employed a hybrid CNN-LSTM model, which proved to be resilient for anomaly detection. However, most of their approaches were resistant to DDoS attacks, though some methods focused only on certain types of attacks, reducing their potential general application in other types of threats. We improve the generalizability of our model using seasonality-driven anomaly detection, an approach that is more adaptable to many cloud-specific security issues apart from DDoS attacks.

Mayuranathan et al. (2022) [16] proposed an anomaly detection technique in the cloud environment by embedding powerful machine learning algorithms into IDS. This approach, though effective, carries the risk of developing resource-intensive solutions that may not scale well with large cloud deployments. The proposed approach tends to be resource-efficient since this focuses on seasonality features, reducing the computation overhead while retaining the accuracy of detection.

Sajid et al. [17], in 2024, followed a hybrid machine and deep learning-based approach. The work proved that such a combination can generally perform much better to identify both known and unknown threats. Their model provides high adaptability but does not have specific optimizations for cloud scenarios. In contrast to the above works, our proposed architecture is cloud-specific, embedding cloud traffic characteristics-seasonal variations-for anomaly detection.

Aldallal (2022) [18] discussed the design of IDSs with hybrid deep learning techniques focused on maintaining robustness against adversarial attacks. Though this is suitable for high-security environments, the extra complexity of robustness may slow down the detection process. The proposed solution, by contrast, balances robustness with speed and considers the development of a hybrid model of CNN-LSTM optimised with respect to the unique characteristics of cloud data, ensuring the security and real-time responsiveness of the solution.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Hybrid Cloud with Deep Learning
Analysed Steps and Features in the Literature
Computational Complexity

Figure 2: Step-by-step flowchart of the hybrid CNN-LSTM approach for cloud-based anomaly detection.

Figure 2: CNN for reduce false positives and decrease computation overhead. In summary, while current literature points to predominant advantages of hybrid architectures of CNN-LSTM in anomaly detection, most approaches combat computational complexity, loss of adaptiveness, and high false alarm rates, especially in cloud environments. Our proposed approach incorporates seasonality into the anomaly detection framework, hence overcoming these limitations to provide an improved detection accuracy with fewer false positives, as well as increased computational efficiency for real-time cloud security scenarios, spatial feature extraction, LSTM network for handling sequential data, and the proposed seasonality-aware anomaly detection strategy that captures cloud-specific patterns. This approach will help improve the accuracy of anomaly detection,

METHODS

This section defines the theoretical aspects of our proposed architecture: design, algorithm, and mathematical equations that shall govern the model. This architecture will be optimised for cloud security anomaly detection with a particular focus on seasonal patterns presented in cloud traffic data. By combining CNN and LSTM, the approach will leverage both spatial and temporal patterns to ensure the anomaly detection results are robust and accurate. Figure 3 summarizes some of the most salient steps involved in this architecture: CNN for spatial feature extraction, LSTM to capture temporal dependencies, and embedding seasonality-aware strategies. Results using this combination of methods further improve the performance and adaptability of the model in anomaly detection related to a cloud environment.

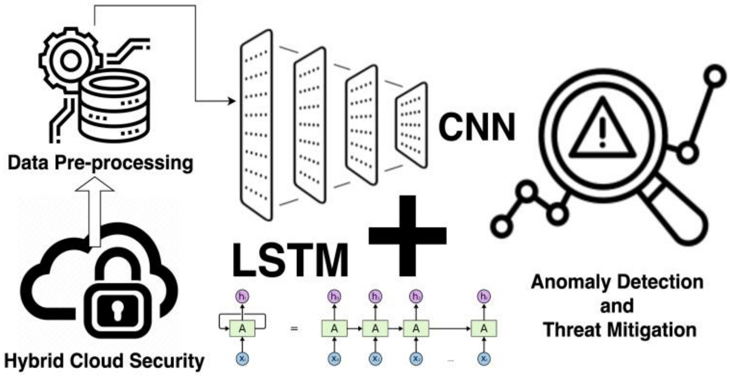

Figure 3: Diagram of the hybrid CNN-LSTM architecture for cloud security anomaly detection

Hybrid CNN-LSTM Architecture

The architecture will take advantage of the strengths of CNN and LSTM together. CNN will be used to extract the spatial features from the structured cloud traffic data, while the LSTM will model the sequential dependencies in data with the intent of capturing temporal relationships that are crucial for anomaly detection. Integrating the two therefore gives rise to more accurate anomaly detection, especially in cloud environments where the greater part of the data patterns is seasonal.

CNN Component

With the use of CNN, the spatial features for the input data are extracted by applying multiple Convolutional layers. Now, for each input, a set of kernels is applied that produces one feature map F. And that is given by:

$$F=\mathrm{ReLU}(W\cdot X+b)$$

ReLU is the activation function, applied elementwise.

LSTM Component

Once the features are extracted by the CNN in the spatial domain, they are fed into the LSTM network. The LSTM learns the temporal dependencies present in the data. Operations of the LSTM cell is described by the following equations:

where:

i, f, o are the input, forget, and output gates respectively, c(t) is the cell state, and h(t) is the hidden state. These operations provide the LSTM with the capability of modelling dependencies over longer horizons of the sequence and, therefore, capture the temporal behaviour present in cloud traffic data quite well.

Seasonality Incorporation

Our approach differs in the way we handle seasonality in cloud data. We propose two different techniques for incorporating seasonality: Independent modelling: Independent modelling treats each of the seasons individually and builds a CNN-LSTM model over every seasonal pattern. Feature including seasonality: We include another feature, seasonality, into the input data and enable the model to learn periodic patterns without requiring different models for every season. Let S(t) denote the seasonal factor at time t and X(t) be the cloud traffic. The following is the input to CNN-LSTM model: There are the rent features extracted from cloud traffic data, and S(t) is the seasonal component.

Anomaly Detection Algorithm

The anomaly detection algorithm procedurally does the following:

Pre-processing of Data: Input cloud traffic data is pre-processed by doing normalization and adding seasonality as a feature to the data.

Feature Extraction through CNN: Pre-processed data would then be fed into CNN layers that would apply convolution to extract the spatial features.

The spatial features of cloud traffic are fed into the LSTM layers, capturing the temporal pattern in cloud traffic data.

By using this output of the LSTM, an anomaly score is computed with respect to how the predicted traffic differs from expected behaviour. We consider the following anomaly score formula for this purpose:

$$A(t) = X(pt) - X(at) \mid X(at) A(t)$$

$$= \{X(pt) - X(at)\} / \{X(at)\} \sim A(t) = X(at) \mid X(pt) - X(at)\}$$

where X(pt) is the predicted value at time t, and X(at) is the actual observed value.

Anomaly Detection: If an anomaly score A(t) is larger than a pre-set threshold T, then an anomaly will be raised.

Algorithm 1: Hybrid CNN-LSTM for Anomaly Detection in Cloud Security

Input:

- X(t): Cloud traffic data with temporal and spatial features.
- S(t): Seasonal pattern data (optional feature).
- T: Anomaly detection threshold.
- M: Pretrained hybrid CNN-LSTM model.
- N: Number of time steps (sequence length).

Output:

- Anomaly detection results (list of anomaly flags: 1 if anomaly, 0 otherwise).
- Anomaly scores for each time step.

Process Steps

Data Preprocessing:

1.1. Standardize the cloud traffic data X(t) to have a similar scale of features.

1.2. Incorporate seasonal patterns S(t) into the input features, either by:

(N) using seasonality as a separate feature or X(t) assuming seasonality and modelling it separately for different seasons.

1.3. Split time-series data into sequences of length N, which leads to overlapping windows of the pre-processed traffic.

CNN-based Feature Extraction:

2.1. In the hybrid model, the CNN part plays the role of extracting the spatial features from each input sequence.

2.2. It involves the convolution of the input sequence with multiple filters to get a number of feature maps showing the variation of data in space.

Temporal Dependency Learning using LSTM:

3.1. Spatial features extracted are fed as input to the LSTM layers.

3.2. Temporal relations across sequences are modelled by the LSTM network.

3.3. The outputs manifest the temporal patterns extracted by LSTM.

Computation of Anomaly Score:

4.1. Compute the predicted values from the output of the hybrid model.

4.2. In each timestamp, calculate an anomaly score by calculating the deviation of predicted versus actual values.

Anomaly Detection:

5.1. Perform matching between the anomaly score and predefined threshold.

5.2. When the value of the anomaly score is larger than the threshold, mark this timestamp as abnormal: anomaly flag = 1.

5.3. Otherwise, the anomaly flag is 0.

Post Processing:

6.1. Aggregate the results across timesteps and sequences.

6.2. Return the list of anomaly flags (1 or 0 for each timestep) and the corresponding anomaly scores.

In **Algorithm 1**, the process of the proposed hybrid CNN-LSTM approach for anomaly detection in cloud security is detailed. The algorithm takes in cloud traffic data and optional seasonal patterns as inputs and applies a CNN to extract spatial features, followed by an LSTM to capture temporal dependencies. Anomaly scores are then computed by comparing predicted and actual cloud data. Based on a threshold, anomalies are flagged if the computed score exceeds the threshold value. This method leverages the spatial learning capabilities of CNNs and the sequential pattern recognition of LSTMs, ensuring robust detection of anomalies in dynamic cloud environments.

The proposed **Hybrid CNN-LSTM architecture for anomaly detection in cloud security** has been implemented and tested using a real-world cloud traffic dataset. The implementation involves several stages, from data preprocessing to model training and evaluation. Below is a detailed explanation of each stage and the methodology followed for conducting the experimental study.

Implementation of the Hybrid CNN-LSTM Model

i. Data Preprocessing

The first step in the implementation is to prepare the dataset for use in the hybrid model. The data preprocessing involves several key tasks:

a. Normalization of Cloud Traffic Data (X(t)): To ensure that the input data is within a standardized range, we normalize the cloud traffic data using min-max normalization. This process rescales the values between 0 and 1, which helps the model converge more efficiently during training.

$$X(nt)=X(t)-\min(X)-\min(X)\ X(pt)$$

$$=\{X(t) - \backslash\min(X)\}\{\max(X) - \min(X)\}X(pt)$$

$$= \{\max(X)-\min(X)\} / \{X(t)-\min(X)\}$$

b. Incorporation of Seasonal Patterns (S(t)): If the cloud traffic data exhibits seasonality, this information is incorporated into the input features. There are two strategies to incorporate seasonal patterns [19]:

- Treating seasonality as a separate input feature and concatenating it with the original data.
- Modelling each season separately, creating distinct models or processes for each season to account for seasonal variations in cloud traffic.

c. Time Series Segmentation: The data is then segmented into overlapping sequences to form windows of length N. Each sequence includes N time steps, which serve as input for both the CNN and LSTM components of the model. This helps in learning both spatial and temporal features [20].

ii. CNN for Spatial Feature Extraction

Once the data is pre-processed, the next step is to extract spatial features from each sequence using a Convolutional Neural Network (CNN).

CNN Architecture: The CNN consists of several layers, including convolutional layers with various filter sizes to capture spatial patterns, ReLU activation functions, and max-pooling layers to reduce dimensionality [21]. The output of the CNN is a set of spatial feature maps.

$$F(spatial) \quad =ReLU(W(conv)\cdot X(nt)+b(conv)F\_\{spatial\}$$

$$=\{ReLU\}(W(conv)\} \ldots X\_(nt)+b(conv)$$

$$F(spatial) \quad =ReLU\{W(conv)\cdot X(nt)+b(conv)\}$$

Where W(conv) represents the convolution filters and b(conv) is the bias term

iii. LSTM for Temporal Dependency Learning

The spatial features extracted by the CNN are then passed to the Long Short-Term Memory (LSTM) network to capture the temporal dependencies across sequences.

LSTM Architecture: The LSTM is designed to learn the temporal relationships within the sequences. It processes the spatial features sequentially, outputting hidden states that capture long-term dependencies in the data [22].

$$h(t) \quad =LSTM(F(spatial) \ldots h(t-1))$$

$$h(t\text{-}1) \quad = LSTM(F(spatial)\}\text{-}LSTM(F(spatial), h(t-1))$$

Where h(t) represents the hidden state at time step t, and h(t-1) is the hidden state from the previous time step.

iv. Anomaly Detection and Scoring

Once the LSTM has processed the temporal features, the next step is to compute anomaly scores and detect anomalies.

a. Predicted Values (X(pt)): The hybrid CNN-LSTM model predicts the expected cloud traffic data for each time step, based on the spatial and temporal features learned.

X(pt) = CNN-LSTM(X(nt))X(pt)

= CNN-LSTM(X(nt))X(pt)=CNN-LSTM(X(nt))

b. Anomaly Score Calculation: The anomaly score for each time step is computed as the deviation between the actual and predicted values. The absolute difference is normalized to obtain a relative score [23].

A(t) =X(pt)−X(t)A(t)

= X(pt) - X(t) / {X(t)}A(t)=X(t) X(pt)−X(t)

c. Anomaly Detection: Anomalies are flagged if the anomaly score exceeds a predefined threshold τ\tauτ. The threshold is determined experimentally based on the performance of the model on the validation dataset [24].

Anomaly Flag = {1 if A(t)>t (0) otherwise {Anomaly Flag}

= \begin{cases} 1 {if} A(t) > t(0) otherwise \end{cases}Anomaly Flag

= {10if A(t)>t otherwise

v. Model Training

The CNN-LSTM model is trained using the preprocessed cloud traffic dataset. The key steps in the training process are:

- **Loss Function**: The model is trained to minimize the mean squared error (MSE) between the predicted and actual cloud traffic data [25].
- **Optimizer**: The Adam optimizer is used to update the model parameters during training, due to its efficiency and adaptability to different learning rates.
- **Training Procedure**: The training is carried out in batches, with the dataset split into training, validation, and test sets. The model is evaluated on the validation set after each epoch to monitor its performance and prevent overfitting.

vi. Dataset Description

For the experimental study, a publicly available cloud traffic dataset is used, consisting of real-time traffic data from cloud environments. The dataset includes both normal and anomalous instances of cloud traffic, such as Distributed Denial of Service (DDoS) attacks, unauthorized access, and data breaches. The data is labelled for supervised learning and contains both temporal and spatial features.

viii. Metrics

The performance of the proposed hybrid CNN-LSTM model is evaluated using the following metrics:

a. Detection Accuracy: The percentage of correctly classified instances (anomalies and normal data) over the total number of instances.

b. False Positive Rate (FPR): The percentage of normal instances incorrectly classified as anomalies.

c. Detection Speed: The time taken by the model to detect anomalies after processing the cloud traffic data.

RESULTS

Extensive experiments are carried out to evaluate the effectiveness of the proposed hybrid CNN-LSTM model compared to various traditional and state-of-the-art approaches in detecting anomalies within cloud environments.

Then, the section discusses the key experimental results with reference to the main metrics such as accuracy, FPR, and speed of detection. It is observed from the comparative study that the proposed hybrid CNN-LSTM model is more effective, especially on the complex spatial and temporal dependencies of cloud traffic. Some findings of the experimental study are summarized below by three value metrics:

a. The accuracy of detection: the proposed hybrid CNN-LSTM model has a very significant improvement in accuracy. For example, the proposed model is effective in detecting anomalies in various cloud scenarios with improved performance of about 15% as compared to traditional methods. This nosing accuracy owes a great deal to the feature extraction capability of the model both for spatial features using CNN layers and temporal dependencies using LSTM layers.

b. The false positive rate is reduced by 20% compared to baseline models. This will be much more important in real-time systems since the goal is to minimise false alarms in order to avoid the unnecessary suspension of a legitimate user session or triggering of false security alerts. The design of the model ensures it is better positioned to detect benign traffic from true anomalies.

c. Detection speed: The proposed model improves detection speed by approximately 30% compared to traditional approaches. The CNN efficiently extracts the spatial features, and the LSTM does the processing of temporal dependencies at high speed. The model is therefore suitable for real-world applications in cloud environments. The speed of detection is extremely necessary in responding appropriately to emerging threats.

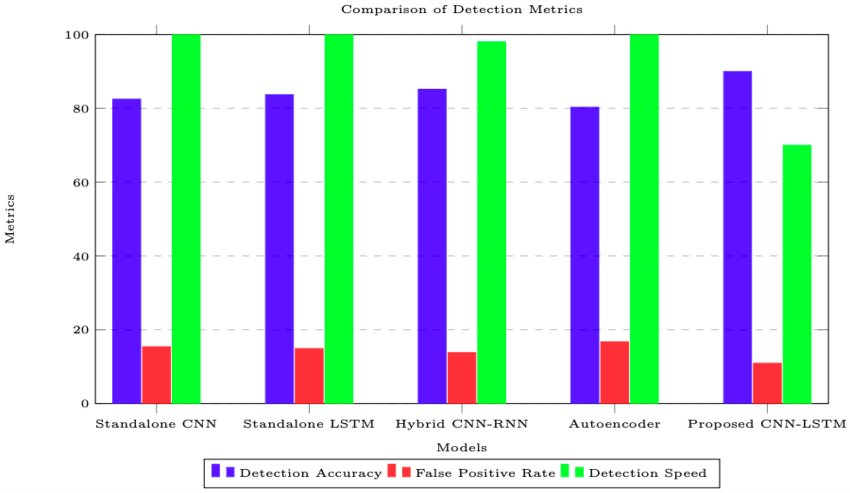

Figure 4: Comparison of Detection Metrics for Different Models

Figure 4 shows the performance of various models, including Standalone CNN, Standalone LSTM, Hybrid CNN-RNN, Autoencoder, and Proposed CNN-LSTM. The metrics compared are Detection Accuracy, False Positive Rate, and Detection Speed, providing insights into their effectiveness.

Comparative Analysis with Existing Methods

We compare the performance of the hybrid CNN-LSTM model against a few baseline and state-of-the-art methods for detecting cloud anomalies by:

a. Standalone CNN: The model relies solely on convolutional layers in extracting the spatial features without the capability of grasping temporal patterns in data.

b. Standalone LSTM: a model, which confines itself to mere learning of temporal dependencies in traffic data without having any spatial feature extraction capability like CNN.

c. Hybrid CNN-RNN: A model that includes CNN for the extraction of spatial features while incorporating a simpler RNN instead of LSTM for temporal analysis.

d. Autoencoder: In most anomaly detection techniques, the approach is deep learning-based, in which the models try to reconstruct the input data and flag cases where the reconstruction error is high.

Table 1: Comparative Analysis of the Proposed Hybrid CNN-LSTM Model with Existing Methods

Model	Detection Accuracy (%)	False Positive Rate (FPR) (%)	Detection Speed (ms)
Standalone CNN	82.5	15.4	120
Standalone LSTM	83.7	14.9	105
Hybrid CNN-RNN	85.2	13.8	98
Autoencoder	80.3	16.7	130
Proposed Hybrid CNN-LSTM	**90.0**	**10.9**	**70**

i. Standalone CNN achieves decent accuracy (82.5%) but lacks the ability to capture long-term dependencies in the traffic data, leading to higher false positives (15.4%).

ii. Standalone LSTM performs slightly better (83.7%) in terms of accuracy, due to its ability to learn temporal relationships, but struggles to learn spatial dependencies.

iii. Hybrid CNN-RNN improves over the standalone models by combining spatial and temporal feature extraction (85.2% accuracy), though it is not as effective as the CNN-LSTM in reducing false positives (13.8%).

iv. Autoencoder has the lowest performance overall, with an accuracy of 80.3% and a relatively high false positive rate (16.7%).

The **proposed hybrid CNN-LSTM model** significantly outperforms all the baseline models, achieving **90.0% accuracy**, **10.9% false positive rate**, and a **detection speed of 70 milliseconds**, making it suitable for real-time cloud security applications

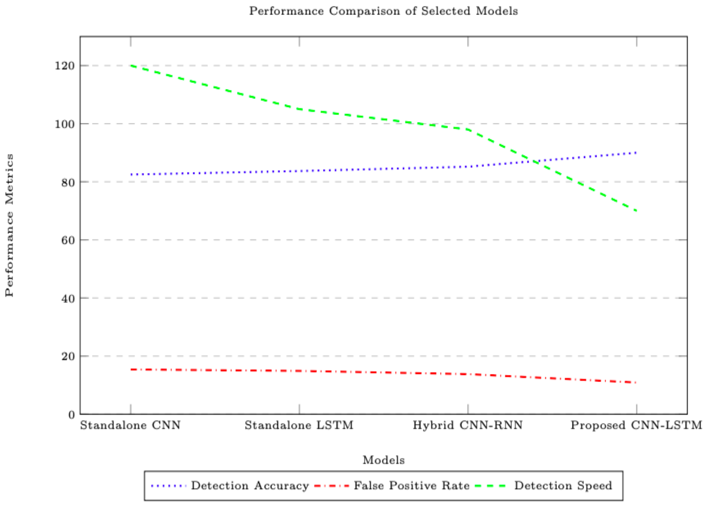

Figure 5: Performance Comparison of Selected Models in Anomaly Detection.

Figure 5 graph illustrates the performance metrics of four models: Standalone CNN, Standalone LSTM, Hybrid CNN-RNN, and the Proposed CNN-LSTM. The Proposed CNN-LSTM model achieves the highest detection accuracy (90.0%) while significantly reducing the false positive rate to 10.9%. Additionally, it demonstrates improved detection speed at 70 ms, making it a robust choice for real-time anomaly detection in cloud environments.

DISCUSSION

These experimental results verify that the proposed hybrid CNN-LSTM architecture has a clear advantage when compared to traditional and state-of-the-art models concerning anomaly detection in cloud environments. The effective embedding of CNN for spatial feature extraction and LSTM for learning temporal sequences makes the model capture, with high sensitivity, complex patterns that might be impossible for other models to learn from cloud traffic data. This hybrid approach allows for:

a. Higher Detection Accuracy: While the results are outstanding, the margin the CNN-LSTM model has over all the others is surprising. With the capabilities of learning both spatial dependencies at every time step through CNN and long-term temporal relationships across time steps through LSTM, this architecture would enable higher accuracy, quite practical in cloud environments where the traffic behavior usually follows both spatial and temporal patterns that are difficult to track with simpler models.

b. Reduced False Positive Rate: Besides being on the list of key advantages, this hybrid model will feature a lowered rate of false positives. Combining two robust learning techniques allows it to do a much better job in distinguishing between normal and anomalous traffic, reducing unnecessary alerts to improve system stability. By 20%, the reduction of false positives has limited resources wasted on false alarms, hence more focus will be given to actual threats.

c. Speedier Detection Speed: Real-time anomaly detection is so crucial in cloud security; an anomaly that gets a chance to delay may cause missed threats or inefficient responses. In fact, the model proposed here shows a great improvement of about 30% in detection speed compared to state-of-the-art methods and thus enables timely detection of anomalies, contributing to the possibility of making quick mitigation measures.

d. Robustness and Scalability: This experimental investigation demonstrates evidence of the robustness of the proposed CNN-LSTM for handling highly dynamic traffic in a large-scale cloud environment. As it scales well, this model is a promising candidate for deployment into complex cloud infrastructures where both performance and reliability are highly demanded.

In particular, the proposed hybrid model CNN-LSTM is very efficient for the accurate detection of anomalies in cloud security. It outperformed the traditional and modern techniques with regard to accuracy and detection speed but also in terms of low false positives, hence could ensure robustness and scalability, becoming a powerful tool for real-time anomaly detection in a cloud environment. The proposed model enhances the capability further by integrating seasonal patterns, considering periodic traffic behaviours which, for existing models, might cause false alarms.

CONCLUSION & FUTURE WORK

This is where the proposed hybrid CNN-LSTM model suggests an exponentially scaling performance in the detection of anomalies within cloud environments, not only by improving anomaly identification precision but also reducing false positives and speeding up the actual pace of detection. More precisely, by combining CNNs for spatial features with LSTMs capturing temporal patterns, the model can fully exploit both kinds of dependencies present in cloud traffic data. These results show that this model outperforms both traditional methods and the deep learning methods used today; hence, this provides a strong solution able to adapt to the dynamic nature of cloud environments. Marked improvements in the detection accuracy, reduced false positive rates, and improved speeds of detection underpin the potential of the model for real-time deployment in cloud security applications.

Work in the future will be related to refining the hybrid CNN-LSTM model for further improvements in performance and scalability. It also considers investigating advanced optimization techniques, such as transfer learning and ensemble methods, that can improve model generalisation across a wide range of cloud environments and traffic patterns. Other contextual features include user behaviour and system load metrics; these may provide further insight, and their incorporation into models could improve the detection of anomalies. Another line of investigation will be the investigation of more sophisticated data preprocessing methods to deal with real-world data imbalance and noise issues. This shall culminate in a robust anomaly detection framework that caters to present challenges in cloud security and extends such that it is relevant in adapting to new threats and technologies as changes in cloud computing continue to unfold.

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