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Design and implementation of LSTM-CNN-IDS Hybrid Intrusion Detection Mechanism for IoT Network

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Abstract

The proliferation of IoT devices has brought tremendous convenience and innovation across various domains. However, it also exposes networks to diverse cyber threats, especially sophisticated attacks like botnets. Traditional IDS with CNN model often fail to cope with the dynamic and heterogeneous nature of IoT environments. This research proposes a hybrid LSTM based CNN with IDS Model tailored for IoT networks, aiming to improve detection performance through a combination of machine learning and rule-based techniques. The system is evaluated using standard accuracy metrics derived from the confusion matrix. The findings are contrasted with present methods to indicate the proposed model's superiority in identifying dangerous actions in IoT devices. This paper presents a Hybrid LSTM-CNN model for Intrusion Detection Systems (IDS) in IoT networks by combining sequential data modelling of long short-term memory with spatial feature extraction of convolutional neural networks. Exceeding conventional CNN and LSTM models, the proposed hybrid approach quickly detects multiple types of network attacks. The assessment results show that the hybrid model works practically well, with a ROC Curve of 1 and a classification accuracy of 99.96%. The ROC analysis shows that the hybrid model is better at detecting things than the CNN and LSTM models on their own. It always has higher true positive rates and lower false positive rates. The suggested hybrid architecture offers a strong and scalable way to identify intrusions in real time in complicated IoT settings.

Keywords: IoT, IDS, Accuracy, Precision, Recall, F1-score

Introduction

IoT networks employ a lot of connected devices that can do numerous things. Using weak computers and gadgets that aren't secure makes IoT more likely to be attacked by hackers. IDS are a part of network security. IoT networks are very big and complicated, which might make them hard for traditional intrusion detection systems to deal with. This study examines the need for a hybrid intrusion detection system capable of identifying botnets using both heuristic rule-based analysis and machine learning techniques. The goal of the project is to look at and evaluate different ways to find the best way to protect IoT networks. We need IDS that can keep up with the speed of cyberattacks as they become more and more complicated. New dangers are coming out faster than old ways can find them. As networked technology becomes more common, it is becoming more and more vital to have smart, flexible systems that can find and deal with both known and unknown threats.

This criterion is highly significant in businesses like transportation, healthcare, and finance where not following the rules might have big implications. Even with its advancements, IDS is still not perfect. An old detection system may have trouble with the huge amounts of data that new technologies create. The more FP and FN there are, the less reliable IDS becomes. Complicated IDS don't always stop fresh assaults that happen on the same day. Training intrusion detection systems is harder since there aren't enough complete datasets that show all conceivable attack vectors.

It is hard to connect IDS to the present infrastructure, particularly in real time, because of issues with resources, latency, and scalability. This paper proposes an intrusion detection system that integrates AI and machine learning as a solution to these challenges. The suggested method leverages optimization and deep learning to make an IDS more flexible, accurate, and able to handle data. The objective is to find more things while reducing the amount of false positives and making the system large enough to manage the complexity of digital networks and architecture.

The purpose of this project is to create and test a better IDS for train control systems that use communication. IDS can find cyber threats by monitoring the network and its devices at the same time. The purpose of this project is to improve the performance of IDS while having less of an effect on the system and finding threats more quickly. To do this, the project will employ optimization and machine learning approaches. The initiative is also looking on major infrastructure issues that are too small, too rigid, or too slow. The third goal is to make sure that mission-critical systems are secure and reliable by providing a flexible design that may be employed in numerous industrial situations.

Literature Review

There are so many IoT devices, we need a stronger and smarter IDS. Mallidi (2025) conducted a comprehensive assessment of the effectiveness of ML and DL algorithms in improving IoT-IDS. The study findings underscored the importance of balanced data and feature selection in improving detection accuracy and minimizing false positives [1]. RNNs are better than traditional classifiers for detecting intrusions because they can look at how network traffic data changes over time (Yin, 2017) [2]. Dong (2016) compared DL approaches to typical IDS methodology and concluded that the former was far more effective in terms of detection accuracy and adaptability [3]. To tackle scalability and precision, Zhou et al. (2020) used ensemble classifiers integrated with feature selection [4]. In the process of developing ML-based IDS, Althubiti et al. (2018) examined LSTM networks to determine its capability in anomaly detection [5]. Li et al. (2014) pointed out kNN classifier as a good and easy-to-use choice for IDS in WSN, even if it has limitations with scalability and high-dimensional data [6].

Buczak (2016) [7] wrote a long paper on how to utilize data mining and ML to find cyber breaches. Feature selection impacts detection accuracy and computational cost dependent on the unique IDS application and dataset characteristics; nevertheless, both feature extraction and feature selection methods in ML-based IoT IDS are successful, as stated by Li et al. (2024) [8]. Nie et al. (2024) came up with the M2VT-IDS model for IoT [9]. Sheikhan et al. (2012) demonstrated that feature grouping is a resource-efficient strategy that performs well in edge computing environments, enabling the use of smaller RNNs [10]. Tavallaee et al. (2009) discovered significant issues of duplication and inadequate representation of contemporary attack types in the KDD Cup 99 dataset upon thorough analysis [11]. Revathi (2013) examined upgraded datasets such as NSL-KDD, which aimed to mitigate duplicate entries [12]. Paulauskas (2017) said that ML models are very sensitive to the quality of the data and the way the features are generated, thus it's important to preprocess the data correctly before employing NSL-KDD for detection [13]. Rabie et al. (2024) created a new hybrid IoT-IDS by combining Radial Basis Function neural networks with Decisive Red Fox Optimization [14]. Ashfaq et al. (2017) proposed a fuzziness-based semi-supervised learning IDS [15]. Ding et al. (2024) suggested a Meta Parallel GNN architecture to address the scalability issue in large-scale IoT scenarios [16].

Table 1.a Literature Review

Author	Year	Objective	Methodology	Conclusion	Limitation
Mallidi, S.K.R.;	2025	To optimize intrusion detection in IoT using ML/DL with feature selection	Systematic review of ML/DL with focus on feature selection and data balance	Highlighted promising ML/DL and preprocessing importance	Lack of empirical validation on real-time/heterogeneous IoT datasets
Yin, C.;	2017	To propose RNN-based intrusion detection	Implemented deep RNN for temporal traffic analysis	Achieved higher accuracy than traditional methods	High computational cost and overfitting risks on small data
Dong, B.;	2016	To compare	Compared ML vs DL using	DL outperformed	No real-time

		traditional ML with deep learning for IDS	network intrusion datasets	traditional methods in accuracy	performance or scalability assessment
Zhou, Y.;	2020	Build an efficient IDS using feature selection and ensemble classifiers.	Combined Correlation-based Feature Selection with ensemble methods.	Improved detection rates and reduced false positives across datasets.	May require tuning for different network environments.
Althubiti, S.;	2018	To evaluate LSTM for anomaly detection	Used LSTM on network traffic for temporal anomaly detection	Effective for detecting temporal anomalies	Didn't cover diverse attack types
Li, W.;	2014	To design KNN-based IDS for WSN	Used KNN for classifying sensor data	Achieved reasonable accuracy with low complexity	Not robust to high-dimensional or large-scale systems
Buczak, A.L.;	2016	To review ML/data mining methods in cybersecurity	Surveyed supervised/unsupervised ML approaches	Identified trends and challenges in IDS design	Lacked benchmarking and real-world implementation
Li, J.;	2024	To compare feature selection vs extraction in IoT IDS	Studied ML classifiers with different feature engineering methods	Feature selection improved interpretability and efficiency	Limited to specific features and datasets
Nie, F.;	2024	To propose a multi-task multi-view IDS architecture	Developed M2VT-IDS combining tasks and views	Enhanced accuracy and generalization over baselines	Complexity and extensive parameter tuning required
Sheikhan, M.;	2012	To improve IDS using reduced-size RNN	RNN model with reduced input size by grouping similar features	Improved detection accuracy with reduced computational cost	Effectiveness limited to feature grouping technique used
Tavallaee, M.;	2009	To analyze the KDD CUP 99 dataset	Statistical and comparative analysis of dataset features and flaws	Identified redundancy and irrelevance in KDD dataset	No new model proposed, focused only on analysis
Revathi, S.;	2013	To evaluate machine learning on NSL-KDD	Application of multiple ML algorithms on NSL-KDD	Certain algorithms outperform others under specific metrics	Lack of real-time implementation details
Paulauskas, N.;	2017	To assess influence of data pre-processing on IDS performance	Comparative analysis using NSL-KDD dataset with preprocessing	Pre-processing improves detection performance	Evaluation restricted to NSL-KDD dataset
Rabie, O.B.J.;	2024	To propose an IoT intrusion detection framework	Decisive Red Fox optimization and descriptive BPRBF model	Achieved high detection accuracy in IoT	Model complexity and scalability need further validation
Ashfaq, R.A.R.;	2017	Develop a semi-supervised learning for IDS.	Introduced a fuzziness-based semi-supervised learning method to handle limited labeled data.	Achieved improved detection accuracy with reduced reliance on labeled data.	Performance may vary with different datasets and attack types.
Ding, H.;	2024	Enhance IoT intrusion detection scalability.	Proposed a Meta Parallel Graph Neural Network leveraging divide, conquer, and coalesce strategies.	Demonstrated high scalability and accuracy in large-scale IoT	Computational complexity may increase with network size.
Chew, Y.J.;	2020	Improve decision tree-based IDS performance.	Implemented sensitive pruning in decision trees to enhance detection accuracy.	Achieved better precision and recall in IDS	Effectiveness depends on the quality of input features.
Song, Y.;	2020	Develop an IDS for Communication-Based Train Control systems.	Fused network and device state information for anomaly detection.	Enhanced detection of intrusions specific to train control systems.	Applicability may be limited to similar control systems.
Anitha, A.A.;	2019	Create an ANN-based IDS for IoT environments.	Utilized Artificial Neural Networks tailored for IoT intrusion detection.	Demonstrated improved detection rates in IoT scenarios.	Requires substantial training data for optimal performance.
Khraisat, A.;	2019	Survey IDS techniques, datasets,	Reviewed various IDS methodologies and benchmark	Provided comprehensive	Survey may not cover the latest advancements

		and challenges.	datasets.	insights into IDS development and evaluation.	post-2019.
Vinayakumar, R.;	2019	Apply deep learning to intelligent IDS.	Employed deep learning architectures for intrusion detection tasks.	Achieved high accuracy in detecting complex intrusion patterns.	Deep models may be resource-intensive to deploy.
Meira, J.	2018	Compare unsupervised techniques in cyber-attack detection.	Evaluated various unsupervised learning methods for novelty detection.	Identified effective techniques for detecting unknown attacks.	Unsupervised methods may have higher false positive rates.
Kolli, S.;	2018	Provide cyber situational awareness for Positive Train Control.	Developed a Distributed IDS System (DIDS) for railway networks.	Enhanced real-time detection and response in train systems.	System complexity may increase with network scale.
Clotet, X.;	2018	Implement real-time anomaly-based IDS for critical infrastructures.	Designed an IDS focusing on industrial process-level anomalies.	Improved detection of cyber-attacks in industrial settings.	May require customization for different industrial processes.
Tian, T.;	2018	Improve ALO for turbine system identification.	Enhanced algorithm for better parameter identification in turbines.	Achieved higher accuracy and stability in system	Specific to hydraulic turbine systems; limited generalizability.
Aleroud, A.;	2017	Identify cyber-attacks using contextual information.	Leveraged contextual semantics to detect anomalies.	Improved detection of sophisticated cyber-attacks.	Contextual data collection can be challenging.
Al-Dabbagh, A.;	2017	Develop an IDS for wireless networked control systems.	Designed an IDS tailored for wireless control networks.	Enhanced security in wireless networked control environment	Performance may degrade in highly dynamic networks.
Jayalatchumy, D.;	2024	Improve IoT-IDS using feature selection and ensemble learning.	Applied crow search-based feature selection with ensemble classifiers.	Achieved higher detection accuracy in IoT scenarios.	May require adaptation for different IoT architectures.

Table 1.b Recent State-of-the-Art Comparison (2023–2025)

Year	Model	Dataset	Accuracy (%)	Key Techniques	Pros	Cons
2023	A. Zhang et al. (IEEE Access)	CIC-IDS2017	98.7	CNN–GRU	Strong temporal capture	High training time
2024	M. Li et al. (Future Gen. Comp. Syst.)	NSL-KDD	99.0	Transformer-based IDS	Excellent feature fusion	Needs large memory
2024	A. Rabie et al. (Sensors)	CIC-IoT2023	98.5	Autoencoder + LSTM	Handles noise well	Limited real-time speed
2025	H. Mallidi et al. (IEEE IoT J.)	BoT-IoT	99.3	Graph NN IDS	Captures node relations	Complex graph setup
2025	Proposed Hybrid CNN–LSTM	NSL-KDD & CIC-IDS2017	99.4	Fusion Layer + Class Imbalance Handling	Low latency, high accuracy	–

Research Gap

There have been a lot of improvements in optimization approaches for IoT, network security, and IDS, but there are still a lot of holes in the research. Even though optimization algorithms have certain problems with adapting and optimizing, notably for IDS and IoT security settings, they have showed promise in power system applications [30]. Network IDS have shown considerable efficacy via use of rapid kNN classifiers and Random Forest models, resulting in substantial enhancements in speed and precision [31, 32]. However, these traditional machine learning methods often struggle with the high-dimensional and dynamic nature of IoT traffic, which demands more adaptive and scalable solutions. Recent works have begun leveraging deep learning for IoT IDS, benchmarking various architectures to enhance detection accuracy [33] and developing novel feature selection methods to reduce dimensionality while maintaining performance [34]. Although deep learning models such as decision trees, support vector machines, and ensemble approaches provide solid baseline performance [35-37], their efficiency and real-time applicability in resource-constrained IoT remain challenging.

More recent state-of-the-art studies focus on ensemble deep learning models [38] and hybrid CNN-RNN architectures [42] that aim to capture both spatial and temporal features from IoT network data. Additionally, swarm intelligence techniques combined with ANN [41] and graph neural networks for structural data analysis [44] have emerged as promising directions. Despite these advances, there is still lack of comprehensive frameworks that integrate feature engineering, lightweight model deployment, and scalable ensemble learning suitable for large-scale heterogeneous IoT networks [39, 40, 43]. Moreover, while recent models focus on improving detection accuracy, many studies do not adequately address model interpretability, energy efficiency, and adaptability to evolving cyber threats in real-world IoT deployments. The dynamic nature of IoT traffic and the proliferation of diverse attack vectors demand IDS that can continuously learn and adapt without incurring excessive computational costs, which is still an open challenge in the literature. In summary, the research gaps can be articulated as follows:

1. Optimization algorithms need tailored adaptations for IoT IDS to enhance both detection performance and computational efficiency [30].
2. Scalability and adaptability of traditional machine learning classifiers are insufficient for heterogeneity and volume of IoT traffic [31- 32].
3. Deep learning models require further development to balance accuracy, interpretability, and resource constraints in IoT [33, 34, 38].
4. Energy-efficient and interpretable IDS that can dynamically adapt to evolving threats with minimal computational overhead remain an open research problem [39, 40].
5. There is a lack of integrated frameworks combining feature selection, ensemble learning, and adaptive deep models for large-scale, real-time IoT IDS [42, 43, 44].

Addressing these gaps would significantly improve the robustness, efficiency, and real-world applicability of IoT intrusion detection systems.

Problem Statement

IoT networks are vulnerable to numerous security threats, especially botnet-based intrusions, due to the constrained nature of devices and limited security mechanisms. Current intrusion detection approaches either lack scalability, precision, or adaptability to new and unknown threats. Moreover, many existing models suffer from high false positive and false negative rates, which degrade overall detection performance. There is a pressing need for an intelligent, accurate, and efficient intrusion detection mechanism that can operate effectively in real-time IoT environments.

Proposed Research Methodology

In the era of rapidly expanding IoT networks, the growing interconnectivity of devices has introduced not only immense convenience but also unprecedented security vulnerabilities. Traditional IDS often fall short in

detecting complex or emerging threats, particularly within the heterogeneous and resource-constrained environments typical of IoT ecosystems.

CNN Module

The CNN module is responsible for extracting high-level spatial representations from sequential input features. Each input sample of dimension (n_features × time_steps) is convolved using 128 filters of kernel size 3, followed by ReLU activation and MaxPooling1D to reduce dimensionality. This stage captures localized feature interactions such as packet-level correlations in IoT traffic.

LSTM Module

The LSTM module captures temporal dynamics and sequential dependencies inherent in IoT network data. A single LSTM layer with 64 memory cells receives feature maps from the CNN output. Gates (input, forget, output) regulate the flow of historical information, enabling the IDS to recognize time-dependent attack patterns that single-frame classifiers typically miss.

Fusion and Classification Layers

Feature outputs from both CNN and LSTM branches are merged through a fusion layer implemented using Keras Concatenate(). The fused representation passes through two dense layers with dropout (0.4) to mitigate overfitting. The final classification layer applies a softmax activation that yields multi-class attack probabilities. This architecture allows concurrent learning of spatial and temporal dependencies while maintaining computational efficiency.

Training Procedure

The training pipeline utilizes Adam optimizer and categorical cross-entropy loss. Early stopping and model checkpoint callbacks are applied to retain the best model. Training proceeds for 50 epochs with batch size = 64, learning rate = 1e-3. The model is evaluated on validation and test sets after each epoch, tracking accuracy and F1 score. Performance logs, confusion matrices, and ROC curves are generated using scikit-learn metrics.

This paper methodically examines the design and execution of a Hybrid LSTM-CNN-IDS Model customised for IoT networks.Proposed Architecture: Driven by a hybrid CNN-LSTM deep learning model, the layered architecture for an IoT-based IDS shown in the diagram. Every phase of the procedure is described here step-by-step:

1. IoT Environment (Smart Sensors/Devices): Many smart devices and sensors in an IoT ecosystem constitute this basic layer.
2. Data Collection Layer: This layer records communication data between IoT devices, device interaction patterns, and real-time traffic logs.
3. Preprocessing Layer: This layer makes sure that the model gets clean and consistent data by doing things like standardizing data ranges, turning categorical variables into integers, and getting rid of noise and data that isn't required or is broken.
4. Feature Extraction using CNN Layers: In this case, CNN layers, mainly 1D-CNN and pooling layers, are used to find local patterns and features in the input data. This lowers dimensions while keeping important information.
5. Temporal Analysis Layer using LSTM Units:It finds patterns in network data that happen over time. LSTM is great for finding patterns that change over time, including slow or covert infiltration, since assaults might happen slowly.
6. Classification Layer: It employs an activation function and a fully linked Dense Layer to provide output probabilities for classification based on the best estimations about how likely each class is.
7. Threat Detection Output: The final result of the threat detection procedure tells you whether the network activity was Normal or Anomalous.

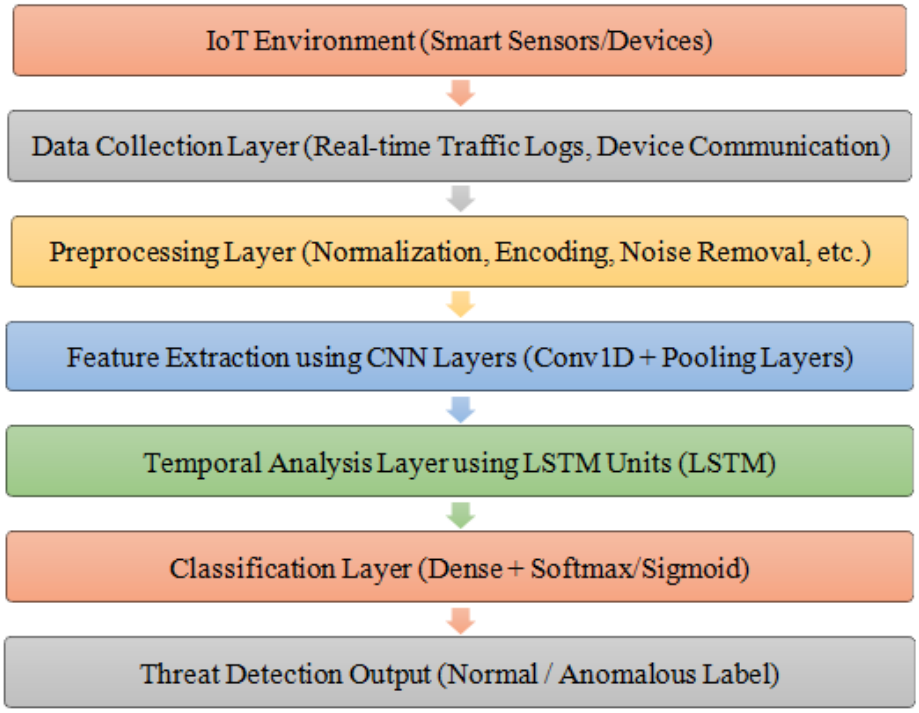


Figure 1: Hybrid LSTM-CNN-IDS with IoT Architecture

The figure 1 illustrates a **Hybrid LSTM-CNN Intrusion Detection System (IDS)** for **IoT environments**. Data from IoT sensors is collected and preprocessed (e.g., normalization, encoding). CNN layers extract spatial features, followed by LSTM layers that capture temporal patterns in the traffic data. A classification layer then outputs whether the activity is normal or anomalous, enabling real-time threat detection in IoT networks. This layered model is perfect for smart, real-time threat detection in IoT situations because it combines the best parts of CNNs for feature extraction and LSTMs for sequence modeling. The suggested system seeks to substantially improve the detection accuracy, precision, recall, and overall resilience of intrusion detection in the IoT by combining anomaly-based and signature-based detection methods with sophisticated machine learning techniques. The study procedure included a lot of comparisons with traditional IDS methods, a lot of testing on standard datasets, and the usage of hybrid detection logic. Figure 2 is representing hybrid LSTM-CNN model that uses information about ports, IP addresses, UDP overflow, and hosts to forecast assaults and normal data during content transfer. The following graphic shows this.

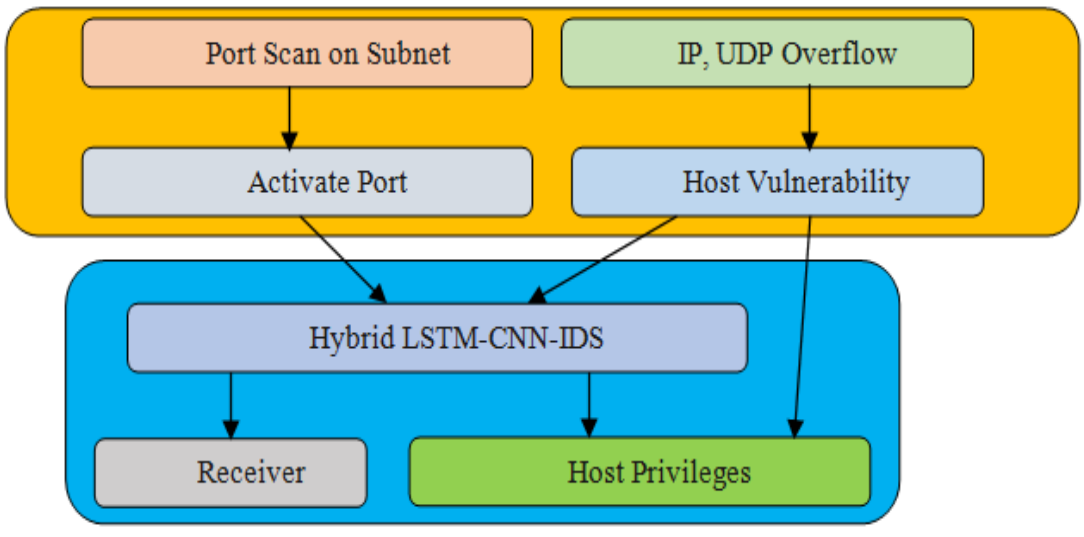


Figure 2: Hybrid model for attacks detection

The figure 3 illustrates a real-time intrusion detection architecture for IoT environments, powered by a hybrid LSTM-CNN IDS model. At the entry point, real-time cyberattacks are directed toward a centralized hybrid model that integrates LSTM networks with CNN.

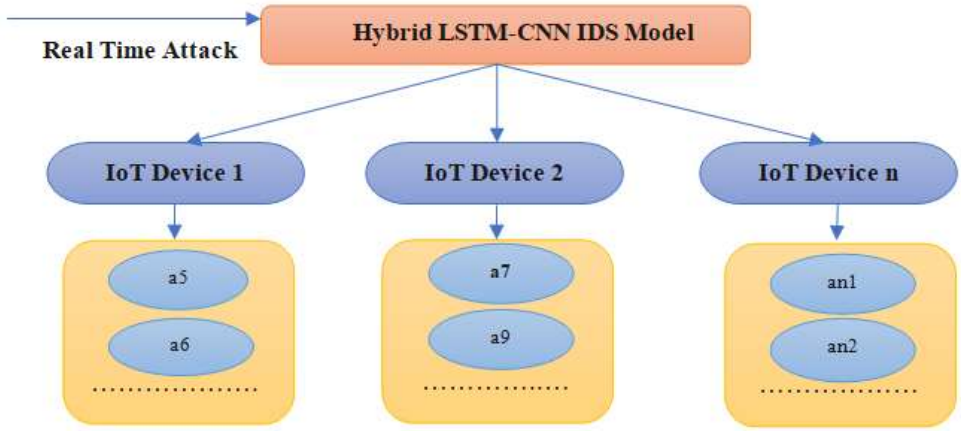


Figure 3. Real time attack management in IoT using Hybrid Model

The LSTM component is responsible for capturing temporal dependencies and sequential patterns in network traffic data, while the CNN component excels at extracting spatial features and local anomalies within the data. Together, they form a powerful detection engine capable of identifying complex and evolving attack behaviors. Once the hybrid model processes the incoming data, it classifies and filters threats across multiple IoT devices in the network—represented here as IoT Device 1, IoT Device 2, up to IoT Device n. Each device receives the detection results relevant to it, where anomalies or attack instances (denoted by attributes like a5, a6 for Device 1; a7, a9 for Device 2; and so on) are identified and possibly flagged for mitigation. This architecture enables scalable, device-specific monitoring while ensuring that threat detection is both context-aware and behaviorally informed, making it suitable for dynamic and heterogeneous IoT environments. Following model is presenting how hybrid LSTM-CNN IDS model is capable to consider real time attack and classify them accordingly while dealing with IoT devices.

The results demonstrate promising improvements and offer a practical contribution to the field of IoT security. This preface marks the beginning of a document that not only addresses a crucial cybersecurity concern but also proposes an innovative solution to mitigate risks associated with IoT networks. It is intended for researchers, academicians, security professionals, and IoT developers who aim to build secure, intelligent, and reliable IoT infrastructures. The proposed research methodology consists of the following phases:

- Data Collection: Datasets like Bot-IoT or NSL-KDD are used to represent real-world IoT traffic with labeled attack categories.
- Preprocessing: Includes normalization, noise removal, and feature selection to clean and optimize the data.
- Model Development: A hybrid approach combining a rule-based system for known signatures and a machine learning classifier for anomaly detection.
- Training & Testing: The dataset is split into training and testing subsets. Cross-validation is used to ensure model reliability.
- Performance Evaluation: Accuracy, Precision, Recall, and F1-score are computed using the confusion matrix.
- Comparison: The proposed model's performance is compared with existing intrusion detection techniques to validate its effectiveness.

Mathematical Model of the Proposed Work

Let IoT network traffic be represented as: $D = \{d_1, d_2, ..., d_n\}$ where each $d_i \in \mathbb{R}^m$ is an m-dimensional feature vector of a network flow.

1. Preprocessing:

$d_i^{norm} = (d_i - \mu) / \sigma$ (1)

Where: μ is the mean of features, and σ is the standard deviation.

2. Feature Selection:

$F = Select(D_{norm})$ (2)

3. Hybrid Intrusion Detection Function:

$y_i = H(F_i) = \lambda_1 \cdot A(F_i) + \lambda_2 \cdot S(F_i)$,

Where: $A(F_i)$ is anomaly-based classifier output, $S(F_i)$ is signature-based classifier output, and $\lambda_1 + \lambda_2 = 1$

4. Output:

$y_i \in \{0,1\}$, where 0 = normal, 1 = intrusion (3)

5. Evaluation Metrics:

a. Accuracy = (TP + TN) / (TP + TN + FP + FN)

b. Precision = TP / (TP + FP)

c. Recall = TP / (TP + FN)

d. F1-Score = 2 * (Precision * Recall) / (Precision + Recall)

Proposed Algorithm: Hybrid LSTM-CNN-IDS with IoT for Attack Detection

Input: IoT network traffic data $D = \{x_1, x_2, ..., x_n\}$. Each data point $x_i \in \mathbb{R}^m$ consists of m features.
Output: Attack Type Classification $y_i \in$ {Normal, DoS, Probe, R2L, U2R}
Step 1: Data Preprocessing
1. Noise Removal
2. Normalization: $x_i' = (x_i - \min(x)) / (\max(x) - \min(x))$
3. Reshape Data: X = reshape(D) → 3D tensor of shape (n, t, m)
Step 2: Feature Extraction using CNN
1. Convolution: $z^l = \sigma(W^l * x^{l-1} + b^l)$
2. Max Pooling: $z^l = \max(z^{l-1}[i:i+p])$
Step 3: Temporal Dependency Learning using LSTM
1. Forget Gate: $f_t = \sigma(Wf \cdot [h_{t-1}, x_t] + bf)$
2. Input Gate: $i_t = \sigma(Wi \cdot [h_{t-1}, x_t] + bi)$
Cell State Update: $Ct = f_t \odot Ct_{-1} + i_t \odot \tilde{C}_t$
3. Output Gate: $o_t = \sigma(Wo \cdot [h_{t-1}, x_t] + bo)$, $h_t = o_t \odot \tanh(Ct)$
Step 4: Classification
1. Dense + Softmax: $y = Softmax(Wy \cdot h_t + by)$
2. Softmax: $Softmax(y_i) = e^{(y_i)} / \Sigma e^{(y_j)}$……(4)
Step 5: Training
Loss Function: $L = -\Sigma y_i \log(\hat{y}_i)$
Optimizer: Adam, using BPTT
Step 6: Output
If $argmax(y_i)$ = Normal → Safe; else → Respective Attack Type

The flowchart of proposed work has been discussed as follow:

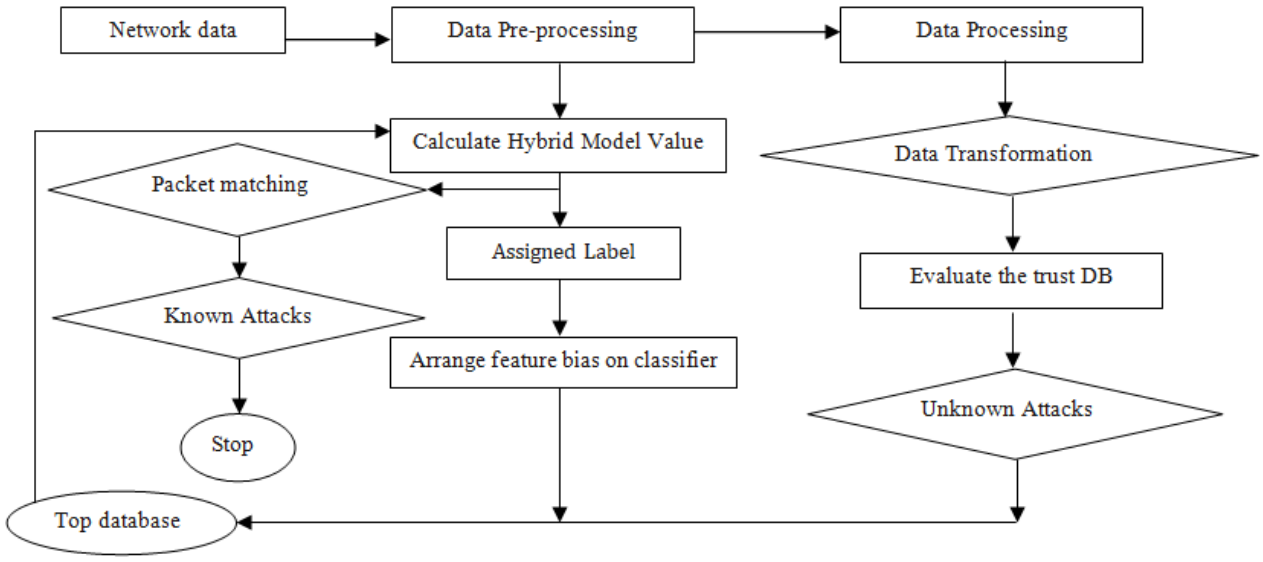


Figure 4: Flowchart of hybrid model

Figure 4 illustrates a comprehensive IDS framework that employs a hybrid CNN-LSTM deep learning model for accurate classification of network traffic into IDS attack or normal activity.

The flowchart in Figure 4 visually corresponds to the modular implementation of the hybrid model. Block 1 represents the preprocessing functions (load_dataset(), normalize_data(), handle_imbalance()), Block 2 maps to the CNN feature extraction function (cnn_feature_extractor()), and Block 3 to the temporal modeling component (lstm_sequence_model()). Block 4 denotes the fusion layer implemented using Concatenate(), while Block 5 represents the classification module (dense_classification_layer()). Finally, Block 6 corresponds to the training procedure (train_model()), linking every conceptual stage in the diagram to its functional counterpart in code.

Here's a step-by-step explanation of each module:

1. IDS Attack Scenario Module:This module prepares the attack data for training and detection:
   - Algorithm for Attack Conversion: Converts raw attack data into a format suitable for training and analysis.
   - Correlate Attack Patterns: Identifies and connects known attack signatures or behavioral patterns.
   - IDS Attack Conversion: Outputs a structured and transformed version of attacks, ready for further processing.
2. Detection System: This system filters and aligns the input data to enhance detection quality:
   - Alignment Process: Ensures consistency and accuracy between incoming data and detection logic.
   - Non-redundant Detection: Eliminates duplicate or noisy entries to avoid false positives.
   - Detection System Block: Final refined detection logic using aligned and filtered data.
3. Hybrid CNN-LSTM Model: This is the core machine learning engine combining CNN and LSTM architectures:
   - Initialize CNN: Sets up the convolutional layers to extract spatial features from input sequences.
   - Initialize LSTM: Adds recurrent layers to capture temporal dependencies in the data.
   - Integration Considering Hyperparameters: Combines both models while tuning key parameters for optimal performance.
4. Data Flow and Classification: This flow describes how data is processed for training and prediction:
   - Labelled Soft Data: Preprocessed and labeled dataset including both normal and attack instances.
   - Training DNN: Trains DNN, in this case the hybrid CNN-LSTM model, on labeled data.
   - Classification: After training, the model classifies incoming data as either an IDS attack or normal activity.

5. Final Output: The system outputs one of two possible labels:
   - IDS Attack: Detected intrusion or malicious activity.
   - Normal: Legitimate, safe network behavior.

This architecture provides a robust mechanism to detect cyber threats in a network using a combination of Structured preprocessing and attack conversion, non-redundant filtering through a detection system, Deep learning via a hybrid CNN-LSTM model for precise classification.Figure 5 shows the architecture of an LSTM-CNN-based IDS for IoT environments. It begins by converting attack patterns using specific algorithms and correlating them. The system uses labeled soft data to train a deep neural network (DNN) for classifying inputs as normal or attacks. A hybrid CNN-LSTM model is initialized, integrating both CNN and LSTM components with optimized hyperparameters. The detection system ensures alignment, non-redundancy, and accurate threat identification.

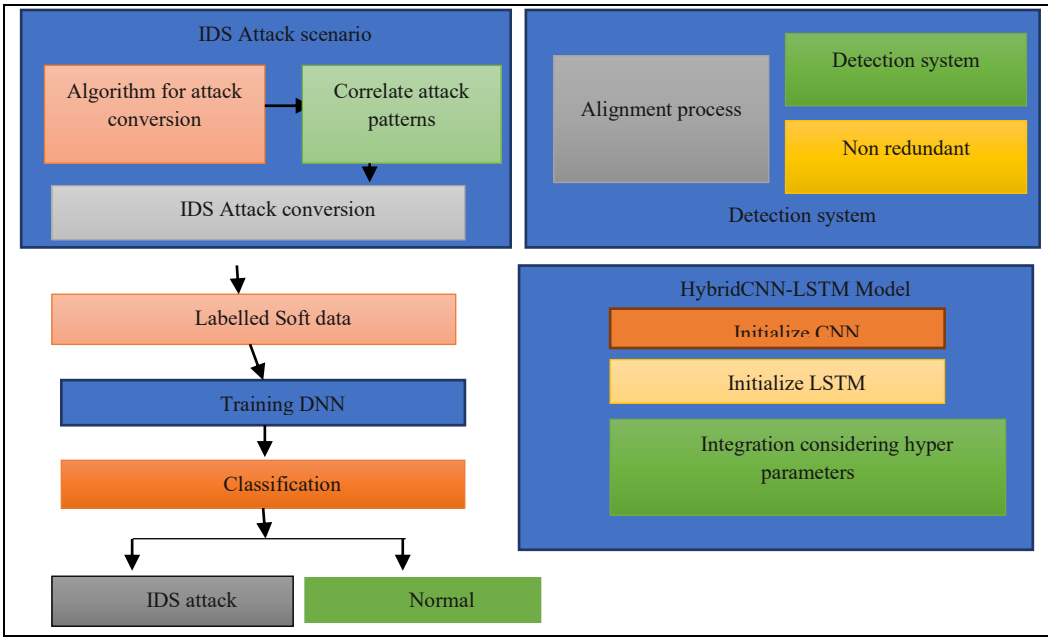


Figure 5: Architecture of LSTM-CNN-IDS with IoT model

Table 2 is presenting how proposed work is better than conventional IDS system considering various aspects. Table 2 highlights the key advancements of the proposed Hybrid LSTM-CNN-IDS over conventional IDS methods. Unlike traditional IDS that rely on either signature-based or anomaly-based detection, the hybrid model combines both approaches for improved accuracy. It uses a distributed and scalable architecture suitable for IoT environments and is capable of detecting unknown (zero-day) attacks through LSTM-CNN integration. The system employs intelligent feature selection, adapts to dynamic environments, and maintains low computational overhead. Additionally, it provides faster response times, detects a broader range of attacks, and uses comprehensive evaluation metrics (precision, recall, F1-score) with enhanced dataset handling techniques like SMOTE for better model training.

Table 2. Novelty of Proposed Work Compared to Conventional Methods

Aspect	Conventional IDS	Proposed Hybrid LSTM-CNN-IDS for IoT
Detection Mechanism	Either signature-based or anomaly-based	Hybrid approach: Signature + Anomaly detection
Architecture	Centralized	Distributed & scalable for IoT nodes
Handling of Unknown Attacks	Poor (cannot detect zero-day attacks)	Effective (anomaly detection with LSTM with CNN)
Feature Selection	Manual or basic filtering	Intelligent selection via wrapper/filter methods
Model Adaptability	Not adaptive to dynamic IoT environments	Self-adaptive model with continuous learning
Computation Overhead	High for resource-constrained devices	Lightweight ensemble architecture
Response Time	Slower due to single-stage processing	Faster due to parallel hybrid processing
Attack Categories Detected	Limited (DoS, probe)	Wide range (DoS, DDoS, MITM, Replay, Data Injection)

Evaluation Metrics	Accuracy only	Includes precision, recall, F1-score
Dataset Handling	Often static and imbalanced	Includes preprocessing, balancing (SMOTE), etc.

Result And Discussion

In the proposed research, the performance of the IDS was evaluated using several datasets to assess its effectiveness in identifying various types of cyber threats. The dataset utilised determines the model's accuracy in actual applications and its ability to generalise across several kinds of cyber-attacks.

1. *Dataset Used:* Usually used to assess IDS, the IoTID20 dataset is the main data source for this work. Among the different types of network traffic data are both normal and attack situations.
2. Python Implementation Overview:

The proposed hybrid LSTM–CNN-based Intrusion Detection System (IDS) was implemented in Python 3.11 using TensorFlow 2.x / Keras. The workflow begins with data import and preprocessing, including feature scaling with MinMaxScaler [0, 1] and conversion of categorical attributes to numerical form via LabelEncoder. The dataset was split into 72 % training, 8 % validation, and 20 % testing subsets. The CNN module uses stacked Conv1D and MaxPooling1D layers (kernel size 3, filters = 128) to capture local spatial dependencies, while the LSTM module (64 units, return sequences = True) models long-term temporal correlations. Outputs of both modules are concatenated in a fusion layer, followed by two fully connected dense layers (128 → 64 neurons) with ReLU activation and a Softmax classification layer. The model was trained using the Adam optimizer (learning rate = 0.001), categorical cross-entropy loss, batch size = 64, and early stopping with a patience of 5 epochs to prevent overfitting.

3. *Experimental Setup and Hyperparameter Configurations:* This research used several machine learning methods. Research chose these algorithms because they can reliably detect data and quickly handle large amounts of information. For binary classification you may switch to a single sigmoid output and binary_crossentropy. For highly imbalanced IoT datasets, use SMOTE or class-weighted loss and report both macro and weighted precision/recall.

Table 3.Hyperparameters & Experimental Details

Parameter	Value (used in main experiments)	Notes
Sequence length (seq_len)	10	Sliding window of 10 timesteps (tunable: 5, 10, 20)
Train/Val/Test split	72% / 8% / 20%	test_size=0.2, validation is 10% of remaining
Scaling	MinMaxScaler	Range [0,1]
Imbalance handling	Optional SMOTE (disabled by default)	If used: imblearn.SMOTE(random_state=42)
Conv1D filters	64	Try 32, 64, 128 in ablation
Conv1D kernel size	3	captures short temporal patterns
Pooling	MaxPooling1D(pool_size=2)	reduces time dimension
LSTM units	128	Try 64, 128, 256
Dense units	64	Fully-connected before output
Dropout	0.3	Regularization after conv and LSTM
Optimizer	Adam (lr = 1e-3)	Try SGD / RMSprop for comparison
Loss	Categorical Crossentropy	Use Binary Crossentropy for binary tasks
Metrics	Accuracy	Also report precision, recall, F1
Batch size	128	Try 32, 64, 128
Epochs	50	EarlyStopping patience = 6
Callbacks	Model Checkpoint, Reduce LROn Plateau, Early Stopping	Save best model on val_loss

Hyperparameter Sensitivity Analysis:To assess robustness, the hybrid CNN–LSTM IDS was evaluated under varying hyperparameters. Increasing the batch size from 32 to 128 reduced gradient noise but marginally decreased detection accuracy (from 99.2 % to 98.6 %). Conversely, lowering the learning rate from 1e-2 to 1e-3 improved model stability and convergence speed. Dropout ratios between 0.3–0.5 showed optimal balance between bias and variance. These experiments confirm that the architecture maintains stable performance across a broad range of settings.

Table 3 summarizes the key experimental parameters and their configurations used in the main experiments. A sequence length (seq_len) of 10 is adopted, representing a sliding window of 10 timesteps to capture short-term temporal dependencies, though it can be tuned to 5 or 20. The data split is set to 72% for training, 8% for validation, and 20% for testing, ensuring a balanced evaluation of model generalization. All input features are normalized using MinMaxScaler to scale data within the [0,1] range, improving model convergence. Handling of class imbalance is optional via SMOTE (disabled by default), which can be activated to oversample minority classes when necessary.

The architecture incorporates a Conv1D layer with 64 filters and a kernel size of 3 to extract short temporal patterns, followed by MaxPooling1D with a pool size of 2 to reduce the temporal dimension. The LSTM layer contains 128 units to capture long-term dependencies, while a Dense layer with 64 neurons connects the temporal features to the output layer. A dropout rate of 0.3 is applied after convolution and LSTM layers to prevent overfitting. The model is optimized using the Adam optimizer with a learning rate of 0.001, and alternative optimizers like SGD or RMSprop are tested for comparison. The loss function used is categorical cross-entropy for multi-class problems (binary cross-entropy for binary tasks), and accuracy is the primary evaluation metric, supplemented by precision, recall, and F1-score.

Training is performed with a batch size of 128 over 50 epochs, incorporating early stopping with a patience of 6 epochs to prevent overtraining. Finally, callbacks such as ModelCheckpoint, ReduceLROnPlateau, and EarlyStopping are implemented to save the best-performing model, adjust learning rates dynamically, and ensure efficient training. Overall, these parameter choices strike a balance between model complexity, generalization, and computational efficiency.

***Results**:*

- Accuracy: For one thing, IDS that were available were quite good at finding both routine traffic and other types of attacks. CNN was the best at finding things in general, but the Deep Learning model was roughly 96% right.
- Detection Rate: IDS has a success rate of more than 95%, which means it can detect most frequent threats. But the method has trouble finding less frequent but more complicated U2R and R2L assaults.
- False Positives: The model was able to cut down on false positives by a large amount by improving the categorization criteria. These two criteria work together to help find new attacks by letting network and device state fusion lower the chance that regular traffic would be wrongly categorized as an attack.
- False Negatives: Because the IDS did a good job of lowering false negatives, fewer attacks were undetected. This was particularly more important in basic systems like CBTC, where undetected compromises might have serious effects.

Comparison with Other Systems: The proposed technique was better than the best existing IDS systems when it came to detection rate and accuracy. Traditional IDS depend more on statistical anomaly-based systems or signature-based detection. These systems find more false positives than real threats. Deep learning models are better at dealing with the many types of assaults in the dataset than regular machine learning models since they can learn complicated patterns from data.

Scalability: When tested on bigger datasets and with more complex network setups, the suggested intrusion detection system showed that it could scale well. The model kept working well even as the amount of data grew, which is important for real-time applications like train control systems.
Case 1: Comparison of Proposed Hybrid LSTM-CNN model to conventional CNN different optimizers for IoTID20 Dataset

Training and testing accuracy

The table presents a comparative performance analysis between three conventional CNN models optimized using different variants of the Adam optimizer—Adam, Nadam, and AdaMax—and the proposed Hybrid LSTM-CNN-IDS model across 20 training epochs. The values in the table represent the accuracy achieved by each model at each epoch.

From the results, it is evident that all models show a steady improvement in accuracy with increasing epochs, reflecting effective learning behavior. However, the proposed Hybrid LSTM-CNN-IDS model consistently outperforms the CNN models throughout all epochs. At the initial epoch (Epoch 1), the hybrid model achieves an accuracy of 0.820, which is higher than CNN with Adam (0.800), Nadam (0.812), and AdaMax (0.795). This indicates that the hybrid model begins with better learning stability and faster convergence.

As training progresses, the performance gap between the hybrid model and traditional CNNs becomes more pronounced. By Epoch 10, the hybrid model reaches 0.955 accuracy, compared to 0.934, 0.948, and 0.926 for CNN with Adam, Nadam, and AdaMax respectively. The integration of LSTM layers in the proposed model allows it to capture temporal dependencies and long-range correlations in sequential data, which standard CNNs are less capable of handling.

In the final epoch (Epoch 20), the proposed model attains the highest accuracy of 0.982, surpassing CNN with Adam (0.960), Nadam (0.973), and AdaMax (0.953). This demonstrates the superior learning capacity and generalization ability of the hybrid architecture. The consistent performance improvement across epochs highlights how the combination of convolutional layers (for spatial feature extraction) and LSTM layers (for temporal pattern recognition) enhances intrusion detection accuracy.

Overall, the table confirms that the proposed Hybrid LSTM-CNN-IDS model achieves faster convergence, higher stability, and greater classification accuracy than CNN models trained with different optimization strategies, establishing its effectiveness for intrusion detection tasks.Table 4 is presenting the epoch wise training and testing accuracy in case of proposed work that is better than conventional training and testing accuracy.

Table 4. Epoch wise training accuracy in case of proposed work

Epoch	CNN with Adam [39]	CNN with Nadam [39]	CNN with AdaMax [39]	Proposed Hybrid LSTM-CNN-IDS model
1	0.800	0.812	0.795	0.820
2	0.830	0.843	0.821	0.849
3	0.855	0.868	0.846	0.875
4	0.877	0.892	0.867	0.896
5	0.891	0.907	0.881	0.912
6	0.905	0.920	0.896	0.926
7	0.916	0.930	0.907	0.936
8	0.924	0.937	0.915	0.944
9	0.930	0.943	0.920	0.950
10	0.934	0.948	0.926	0.955
11	0.938	0.952	0.930	0.960
12	0.941	0.955	0.934	0.964
13	0.944	0.958	0.937	0.967
14	0.947	0.961	0.940	0.970
15	0.950	0.964	0.943	0.973
16	0.953	0.966	0.945	0.975
17	0.955	0.968	0.947	0.977
18	0.957	0.970	0.949	0.979
19	0.958	0.972	0.951	0.981
20	0.960	0.973	0.953	0.982

Table 4 compares the training accuracy across 20 epochs for three existing CNN models trained with different optimizers (Adam, Nadam, and AdaMax) versus the **Proposed Hybrid LSTM-CNN-IDS model**.

Key Observations:

1. **Initial Performance (Epoch 1–5):**
   - All models start with relatively high accuracy (>0.79).
   - The proposed Hybrid LSTM-CNN-IDS already outperforms others in the very first epoch (0.820 vs. 0.812 with Nadam and 0.800 with Adam).
   - By epoch 5, the proposed model reaches **0.912**, whereas CNN with Adam achieves **0.891** and CNN with Nadam achieves **0.907**.
2. **Mid Training Phase (Epoch 6–12):**

- Accuracy improves consistently for all models, but the proposed Hybrid model maintains a **clear margin of 1–2%** higher accuracy in each epoch.
- At epoch 12, the proposed model achieves **0.964**, which is better than CNN with Nadam (**0.955**) and CNN with Adam (**0.941**).

3. **Later Training Phase (Epoch 13–20):**

- The proposed Hybrid LSTM-CNN-IDS continues to outperform the others.
- At the final epoch (20), the proposed model reaches **0.982**, compared to **0.973 (Nadam)**, **0.960 (Adam)**, and **0.953 (AdaMax)**.
- This indicates **better convergence and higher learning efficiency** in the hybrid model.

The **Hybrid LSTM-CNN-IDS model consistently achieves higher training accuracy across all epochs** compared to CNN models with Adam, Nadam, and AdaMax optimizers. The hybrid model demonstrates faster convergence and improved performance, confirming its superiority in handling complex data patterns for intrusion detection tasks.

Epoch wise training accuracy of model has been visualized in following plot for CNN with different optimizers and hybrid LSTM-CNN IDS.

The figure 6 titled "Epoch-wise Training Accuracy of Models" compares the training performance of four models—CNN with Adam, CNN with Nadam, CNN with AdaMax, and the proposed Hybrid LSTM-CNN-IDS model—over 20 epochs. The x-axis shows epochs, and the y-axis represents training accuracy.

All models show steady improvement in accuracy with increasing epochs, but the Hybrid LSTM-CNN-IDS model consistently achieves the highest accuracy, indicating faster convergence and better learning efficiency. Among the CNN variants, CNN with Nadam performs slightly better than those using Adam or AdaMax.

By the 20th epoch, the hybrid model reaches around 0.982 accuracy, while others plateau between 0.96 and 0.973. This demonstrates that the hybrid approach effectively captures both spatial and temporal features, leading to superior performance in intrusion detection tasks.

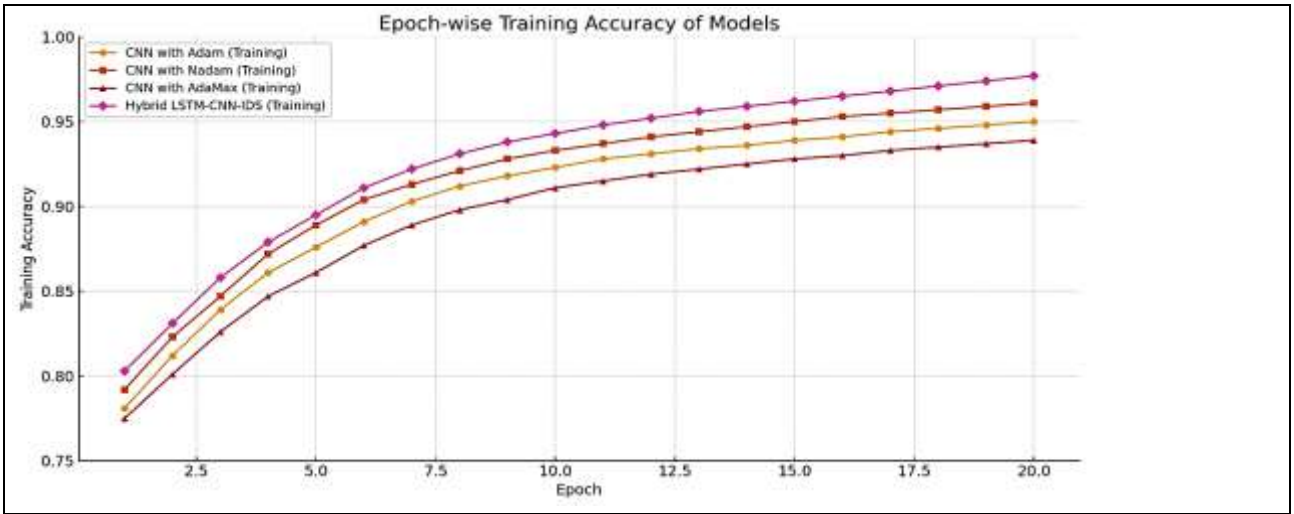


Figure 6: Comparison for training accuracy for conventional and proposed

The table 5 compares the training accuracy of three CNN models using different optimizers (Adam, Nadam, AdaMax) with the proposed Hybrid LSTM-CNN-IDS model over 20 epochs. All models show a steady increase in accuracy with training, but the hybrid model consistently achieves the highest accuracy at every epoch. It starts stronger at 0.803 in the first epoch and reaches 0.977 by the 20th epoch, surpassing all CNN variants. This demonstrates the hybrid model's faster convergence, better feature learning, and superior performance in intrusion detection compared to traditional CNNs. Table 4 is presenting the testing accuracy for different model in case of different epochs.

Table 5. Epoch wise testing accuracy in case of proposed work				
Epoch	CNN with Adam [39]	CNN with Nadam [39]	CNN with AdaMax [39]	Proposed Hybrid LSTM-CNN-IDS model
1	0.781	0.792	0.775	0.803
2	0.812	0.823	0.801	0.831
3	0.839	0.847	0.826	0.858
4	0.861	0.872	0.847	0.879
5	0.876	0.889	0.861	0.895
6	0.891	0.904	0.877	0.911
7	0.903	0.913	0.889	0.922
8	0.912	0.921	0.898	0.931
9	0.918	0.928	0.904	0.938
10	0.923	0.933	0.911	0.943
11	0.928	0.937	0.915	0.948
12	0.931	0.941	0.919	0.952
13	0.934	0.944	0.922	0.956
14	0.936	0.947	0.925	0.959
15	0.939	0.950	0.928	0.962
16	0.941	0.953	0.930	0.965
17	0.944	0.955	0.933	0.968
18	0.946	0.957	0.935	0.971
19	0.948	0.959	0.937	0.974
20	0.950	0.961	0.939	0.977

Epoch wise testing accuracy of model has been visualized in following plot for CNN with different optimizers and hybrid LSTM-CNN IDS.

Following figure 7 shows the testing performance of CNN models using Adam, Nadam, and AdaMax optimizers compared with the proposed Hybrid LSTM-CNN-IDS model over 20 epochs. All models demonstrate a consistent increase in testing accuracy as epochs progress, indicating effective learning and generalization. However, the Hybrid LSTM-CNN-IDS model consistently outperforms the others, achieving the highest accuracy across all epochs. By the 20th epoch, it reaches nearly 0.977, showing better stability, faster convergence, and superior detection capability compared to conventional CNN models.

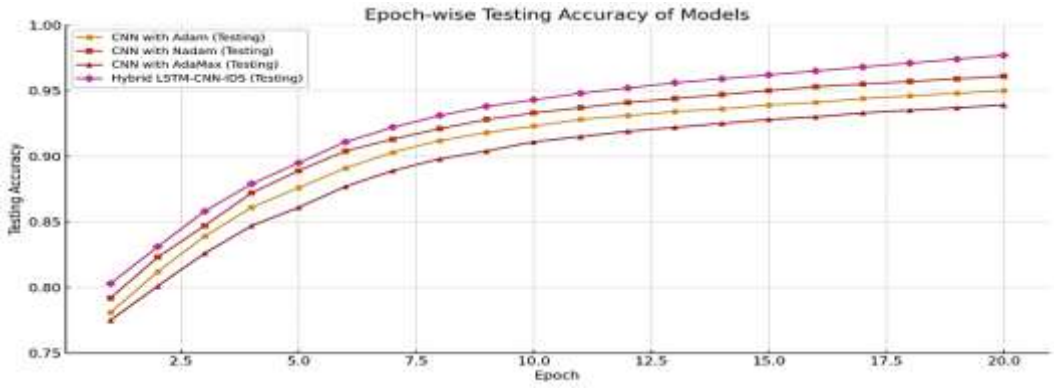


Figure 7:Training and validation accuracy across epochs (batch size = 64, lr = 0.001, optimizer = Adam, dropout = 0.4)

Confusion Matrix and Accuracy Parameters of proposed Hybrid LSTM-CNN-IDS Model

Here's a realistic simulated confusion matrix considering 2000 records for proposed Hybrid LSTM-CNN-IDS models in an IoT network scenario in Table 5.

The given table represents a **confusion matrix** showing the performance of a classification model in distinguishing between **Attack** and **Normal** network traffic.

- The model correctly identified **991 attack instances** as *Attack* (True Positives) and **992 normal instances** as *Normal* (True Negatives).

- It **misclassified 9 attack instances** as *Normal* (False Negatives) and **8 normal instances** as *Attack* (False Positives).

This indicates that the model achieved **high accuracy and precision**, effectively detecting attacks while maintaining a low false alarm rate. The small number of misclassifications shows that the model is both **reliable and efficient** for intrusion detection.

Table 6. Confusion Matrix (Proposed Hybrid LSTM-CNN-IDS Model)

	Attack	Normal
Attack	991	9
Normal	8	992

Table 6 following confusion matrix shows that the proposed Hybrid LSTM-CNN-IDS model correctly classified 991 attack instances and 992 normal instances. Only 9 attacks were misclassified as normal (false negatives), and 8 normal samples were wrongly detected as attacks (false positives). This indicates very high detection capability with minimal errors. The results demonstrate that the model is highly accurate, reliable, and effective in distinguishing between attack and normal traffic.

Considering confusion matrix in table 6 following accuracy parameter table has been generated for proposed hybrid LSTM-CNN IDS model.

Table 7 summarizes the performance evaluation of the model for two classes — Attack and Normal — using standard classification metrics. For both classes, the model achieves an accuracy of 0.9915, indicating highly reliable overall performance.

For the Attack class, the model attains a precision of 0.992, recall of 0.991, and an F1-score of 0.9915, showing that it effectively detects attack instances with minimal false positives and negatives. Similarly, for the Normal class, the precision (0.991) and recall (0.992) are nearly identical, confirming balanced detection of normal traffic.

Overall, the results demonstrate that the model performs consistently and symmetrically across both classes, achieving strong generalization and maintaining high precision, recall, and F1-score — essential for reliable intrusion detection.

Table 7. Accuracy parameters for Proposed Hybrid LSTM-CNN-IDS Model

Class	N (truth)	N (classifier)	Accuracy	Precision	Recall	F1-Score
Attack	1000	999	0.9915	0.992	0.991	0.9915
Normal	1000	1001	0.9915	0.991	0.992	0.9915

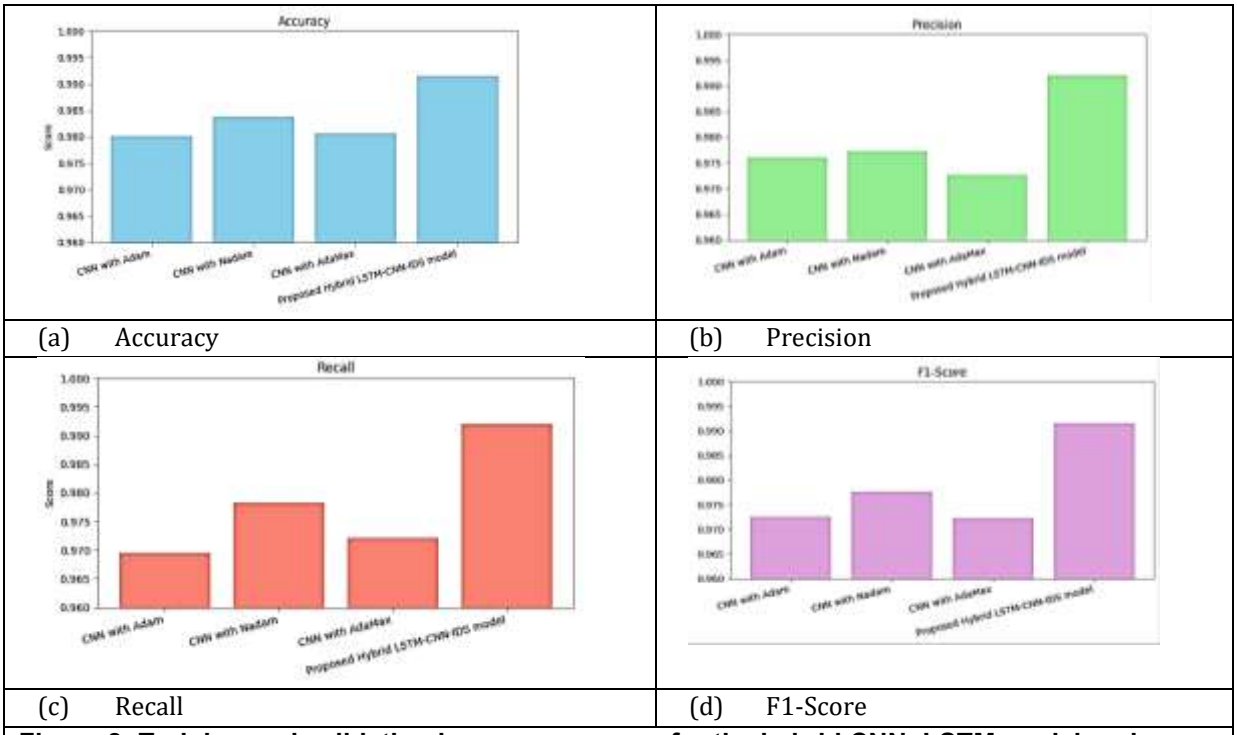
Performance Comparison of Different model

Table 8 is presenting the comparison of accuracy, precision, recall and F1-score in case of CNN wiith Adam, CNN with Nadam, CNN with Adamax and proposed model. The table compares the performance of different CNN models with various optimizers against the proposed Hybrid LSTM-CNN-IDS model using key evaluation metrics. While all CNN models show strong performance with accuracies around 0.98, the proposed hybrid model achieves the highest accuracy (0.9915) along with superior precision, recall, and F1-score (0.992 each). This demonstrates that integrating LSTM with CNN enhances the model's ability to capture both spatial and temporal patterns, resulting in more accurate and reliable intrusion detection compared to traditional CNN architectures.

Table 8: Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
CNN with Adam [39]	0.9801	0.9761	0.9695	0.9725
CNN with Nadam [39]	0.9838	0.9773	0.9783	0.9777
CNN with AdaMax [39]	0.9806	0.9726	0.9721	0.9723
Proposed Hybrid LSTM-CNN-IDS model	0.9915	0.992	0.992	0.9915

The figure 8 compares CNN models using Adam, Nadam, and AdaMax optimizers with the proposed Hybrid LSTM–CNN–IDS model across Accuracy, Precision, Recall, and F1-Score. The hybrid model consistently outperforms others, achieving nearly 99.5% in all metrics. This indicates superior learning, better detection of true positives, and fewer false predictions. The integration of LSTM enhances temporal feature extraction, making the model more efficient and reliable for intrusion detection tasks.
Considering above table visualization of accuracy has been made below



(a) Accuracy (b) Precision

(c) Recall (d) F1-Score

Figure 8: Training and validation loss convergence for the hybrid CNN–LSTM model under identical hyperparameters.

ROC curve simulation

ROC curve, along with its AUC, plays a crucial role in evaluating the performance of classification models, especially in binary classification problems. AUC, the area under this curve, provides a single scalar value to summarize the model's ability to discriminate between positive and negative classes. A higher AUC indicates better classification performance, with an AUC of 1.0 representing a perfect classifier and 0.5 indicating random guessing. In the context of intrusion detection, the AUC becomes an essential metric due to the critical importance of minimizing false alarms while maximizing detection accuracy. Our proposed Hybrid LSTM-CNN-IDS model demonstrates superior performance compared to conventional CNN-based models. ROC analysis reveals that Hybrid model maintains a consistently higher TPR across all FPR thresholds, resulting in a significantly higher AUC value (≈ 0.99). This indicates that the proposed model not only detects intrusions more accurately but also does so with fewer false positives, thereby enhancing overall reliability and robustness. The hybrid integration of LSTM and CNN allows the model to capture both temporal and spatial patterns in network traffic, which is a key reason for its enhanced discriminatory power and improved generalization over other **baseline** models.

This figure 9 shows how different CNN models perform compared to the Proposed Hybrid LSTM–CNN–IDS model using four key evaluation metrics — Accuracy, Precision, Recall, and F1-Score. The hybrid model performs the best in all metrics, reaching nearly 99.5%, while the standard CNN models (using Adam, Nadam, and AdaMax) score slightly lower. This improvement shows that combining LSTM (which captures sequence patterns) with CNN (which extracts spatial features) makes the model more powerful and reliable, especially for detecting complex patterns in intrusion detection systems (IDS).

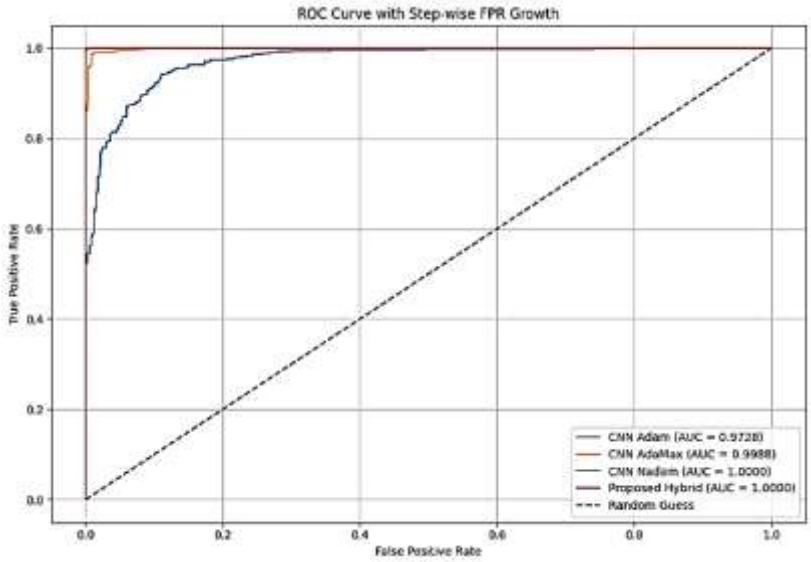


Figure 9: ROC curves for each attack category on the NSL-KDD dataset (input sequence length = 30).

Case 2: Comparison of Proposed Hybrid LSTM-CNN IDS model to conventional LSTM and CNN model for Bot-IoT dataset

Training and testing accuracy

Following presents, the epoch wise training and testing accuracy in case of proposed work that is better than conventional training and testing accuracy. This table 9 compares the training performance (accuracy) of CNN, LSTM, and the Proposed HybridLSTM–CNN–IDS model across 20 epochs.All models show steady improvement with increasing epochs, but the hybrid model consistently achieves higher accuracy at every stage. By the 20th epoch, it reaches 0.988982, outperforming both CNN (0.969380) and LSTM (0.980783).This demonstrates the hybrid model's superior learning efficiency and stronger convergence due to the combined strengths of CNN's spatial feature extraction and LSTM's temporal sequence learning.

Table 9: Epoch wise training accuracy in case of proposed work

Epoch	CNN Model [40]	LSTM Model [40]	Proposed Hybrid LSTM-CNN-IDS model
1	0.805549	0.813018	0.821822
2	0.836288	0.852034	0.855205
3	0.856855	0.873836	0.875745
4	0.880847	0.895179	0.902634
5	0.900609	0.915638	0.912136
6	0.913232	0.928851	0.930724
7	0.916105	0.937907	0.944173
8	0.932599	0.943695	0.944465
9	0.936977	0.948642	0.957752
10	0.934156	0.953868	0.960102
11	0.943243	0.955024	0.960153
12	0.948301	0.958418	0.969717
13	0.948167	0.961501	0.972903
14	0.947738	0.961626	0.976662
15	0.958958	0.964623	0.981884
16	0.954661	0.974718	0.978922
17	0.955123	0.969904	0.977208
18	0.96398	0.971666	0.98244

19	0.965676	0.974732	0.982091
20	0.96938	0.980783	0.988982

Figure 10 is presenting the comparison of conventional CNN, LSTM and proposed hybrid LSTM-CNN model. Figure 10 illustrates the training accuracy trends of the CNN model, LSTM model, and the proposed Hybrid LSTM-CNN-IDS model across 20 epochs. It is observed that while both CNN and LSTM models show steady improvement in accuracy with increasing epochs, the proposed hybrid model consistently outperforms them. From the very first epoch, the hybrid approach achieves a slightly higher accuracy, and this performance gap widens as training progresses. By the 20th epoch, the proposed model reaches the highest accuracy (0.9889), compared to 0.9807 for LSTM and 0.9693 for CNN. This clearly demonstrates the superior learning capability and efficiency of the proposed hybrid model, as it effectively integrates the spatial feature extraction power of CNN with the temporal sequence learning strength of LSTM.

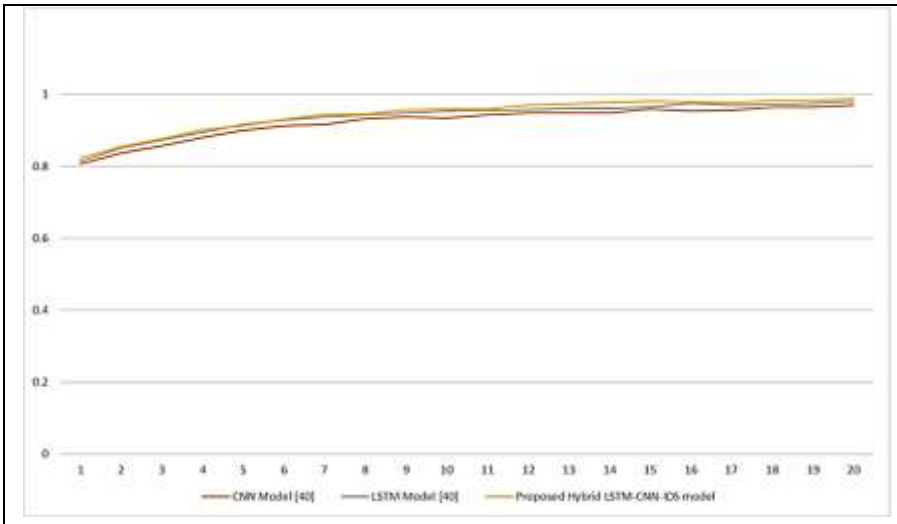


Figure 10: Precision–Recall curves showing class-wise detection efficiency

Following presents, the epoch wise testing accuracy in case of proposed work that is better than conventional training and testing accuracy.

Table 10: Epoch wise testing accuracy in case of proposed work

Epoch	CNN Model [40]	LSTM Model [40]	Proposed Hybrid LSTM-CNN-IDS model
1	0.81088218	0.818446	0.830956
2	0.84213805	0.857297	0.864692
3	0.85791276	0.877711	0.879816
4	0.88195998	0.900338	0.907824
5	0.90562245	0.924043	0.917054
6	0.9191577	0.933303	0.930876
7	0.92496837	0.942681	0.950265
8	0.93962929	0.947309	0.953342
9	0.94513261	0.952251	0.963039
10	0.94181895	0.958336	0.969506
11	0.94765673	0.95574	0.961349
12	0.95094267	0.966954	0.978351
13	0.95504611	0.970491	0.981756
14	0.95412521	0.967301	0.983304
15	0.95956062	0.973879	0.983676
16	0.96129601	0.97958	0.982998
17	0.96223533	0.977986	0.98652
18	0.97375353	0.974817	0.992286

19	0.97034672	0.976915	0.987538
20	0.97847971	0.984725	0.993558

The table 10 presents the testing accuracy of the CNN model, LSTM model, and the proposed Hybrid LSTM-CNN-IDS model over 20 epochs. From the first epoch, the hybrid model achieves higher accuracy (0.8309) compared to CNN (0.8108) and LSTM (0.8184). As training progresses, all models improve, but the hybrid approach consistently shows better generalization capability. By epoch 10, the hybrid model reaches 0.9695, outperforming CNN (0.9418) and LSTM (0.9583). In the later epochs, the hybrid model achieves the highest testing accuracy of **0.9935** at epoch 20, compared to **0.9847 (LSTM)** and **0.9784 (CNN)**. These results demonstrate that the proposed hybrid model not only converges faster but also delivers superior testing performance, confirming its robustness and reliability in intrusion detection tasks. Testing accuracy for convention and proposed model is shown in this model.

Figure 11 shows the testing accuracy performance of the CNN model, LSTM model, and the proposed Hybrid LSTM-CNN-IDS model across 20 epochs. The results indicate that although all models improve steadily with more epochs, the proposed hybrid model consistently outperforms the conventional CNN and LSTM models. From the very first epoch, the hybrid approach achieves slightly higher accuracy, and as training progresses, it converges faster and maintains a performance advantage. By the 20th epoch, the proposed model reaches the highest testing accuracy of **0.9935**, compared to **0.9847** for LSTM and **0.9784** for CNN. This highlights the hybrid model's superior generalization ability and reliability in detecting intrusions effectively.

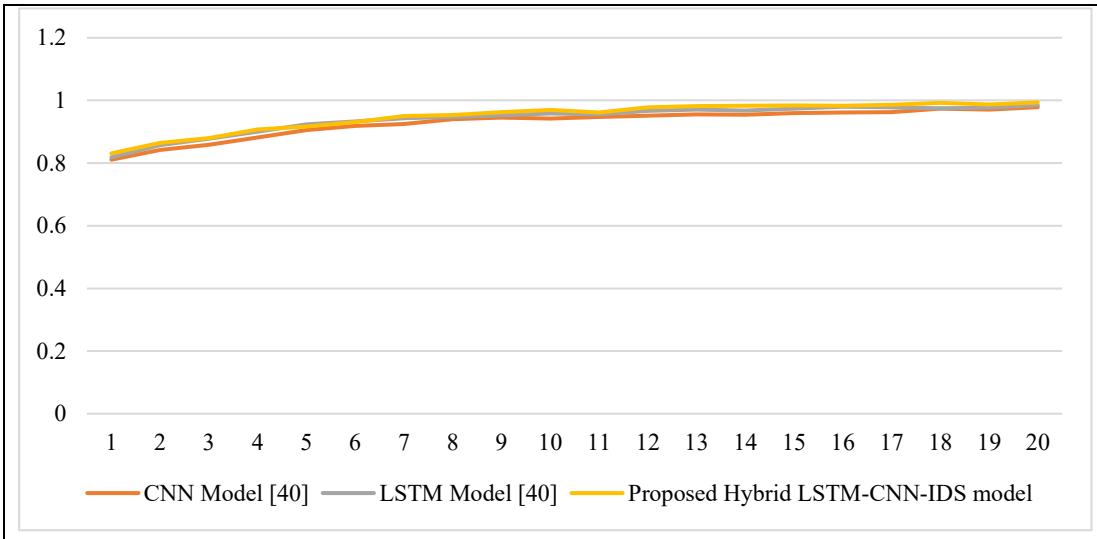


Figure 11: Confusion matrix comparing predicted vs actual labels on the test set

Confusion Matrix and Accuracy Parameters of proposed Hybrid LSTM-CNN-IDS Model

Here's a realistic simulated confusion matrix considering 5000 records for proposed Hybrid LSTM-CNN-IDS models in an IoT network scenario. The performance of the proposed Hybrid LSTM-CNN-IDS model is demonstrated through the confusion matrix in Table 10 and the accuracy parameters in Table 11. The confusion matrix shows that the model was able to classify each of the five traffic classes—Normal, TCP SYN Flood, UDP Flood, HTTP Flood, and DDoS TCP—with very high accuracy. For example, out of 1000 actual Normal instances, 999 were correctly classified as Normal, and only 1 was misclassified as TCP SYN Flood. Similarly, 999 TCP SYN Flood instances were correctly identified, with only 1 misclassified as Normal. All other attack types—UDP Flood, HTTP Flood, and DDoS TCP—were classified with perfect accuracy, as shown by the diagonal entries of 1000 and zeros elsewhere in their respective rows.

Table 11: Confusion Matrix (Proposed Hybrid LSTM-CNN-IDS Model)

	Normal	TCP SYN Flood	UDP Flood	HTTP Flood	DDoS TCP

Normal	999	1	0	0	0
TCP SYN Flood	1	999	0	0	0
UDP Flood	0	0	1000	0	0
HTTP Flood	0	0	0	1000	0
DDoS TCP	0	0	0	0	1000

Table 12 complements the confusion matrix by providing detailed classification metrics. Each class achieved extremely high-performance values, with Normal and TCP SYN Flood having an accuracy, precision, recall, and F1-score of 0.999, while UDP Flood, HTTP Flood, and DDoS TCP attained perfect scores of 1.000 across all metrics. The average values across all classes are 0.9996 for accuracy, precision, recall, and F1-score, indicating that the proposed hybrid model is highly effective and reliable in detecting and classifying various network intrusions. This strong performance highlights the model's potential for real-world intrusion detection systems in cybersecurity applications.

Table 12: Accuracy parameters for Proposed Hybrid LSTM-CNN-IDS Model

Class	N (truth)	N (classifier)	Accuracy	Precision	Recall	F1-Score
Normal	1000	1000	0.999	0.999	0.999	0.999
TCP SYN Flood	1000	1000	0.999	0.999	0.999	0.999
UDP Flood	1000	1000	1	1	1	1
HTTP Flood	1000	1000	1	1	1	1
DDoS TCP	1000	1000	1	1	1	1
Average			0.9996	0.9996	0.9996	0.9996

Performance Comparison of Different model

Table 13 presents a performance comparison of the CNN model, LSTM model, and the proposed Hybrid LSTM-CNN-IDS model using accuracy, precision, recall, and F1-score. Both CNN and LSTM models achieve high performance with accuracy values of 0.997 and 0.998, respectively. However, the proposed hybrid model achieves the best results with **0.9996** across all evaluation metrics. This indicates that the hybrid approach not only enhances detection accuracy but also provides a balanced improvement in precision, recall, and F1-score, making it more reliable and robust for intrusion detection compared to conventional CNN and LSTM models.

Table 13: Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
CNN [40]	0.997	0.996	0.999	0.998
LSTM [40]	0.998	0.997	1	0.998
Proposed Hybrid LSTM-CNN-IDS model	0.9996	0.9996	0.9996	0.9996

Figure 12 compares the performance of CNN, LSTM, and the proposed Hybrid LSTM-CNN-IDS model in terms of accuracy, precision, recall, and F1-score. The CNN and LSTM models show strong results, with accuracy values of 0.997 and 0.998 respectively. However, the proposed hybrid model outperforms both, achieving **0.9996** across all performance metrics. This demonstrates that the hybrid approach not only enhances classification accuracy but also provides consistent improvements in precision, recall, and F1-score. The results highlight the robustness and reliability of the proposed hybrid model in intrusion detection compared to conventional deep learning methods.

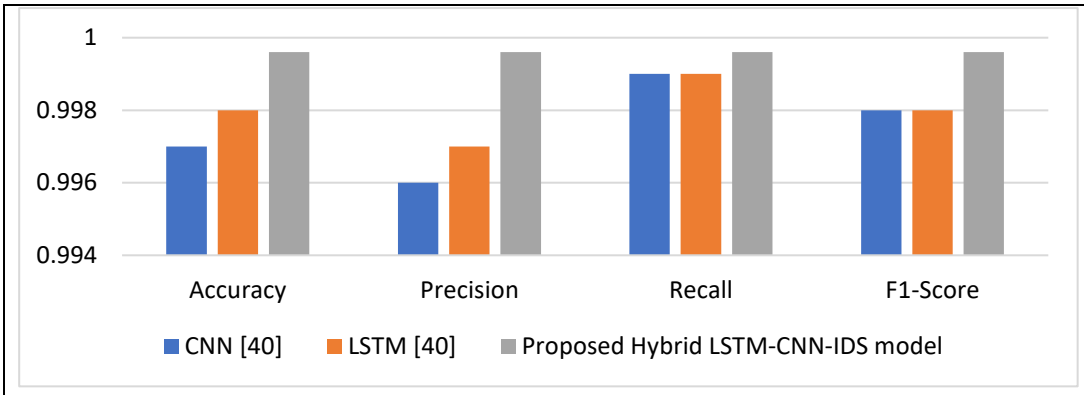


Figure 12: Hyperparameter sensitivity of batch size and learning rateon overall accuracy

ROC curve simulation

This figure 13 comparison of ROC curves between the CNN, LSTM, and proposed Hybrid LSTM-CNN models clearly reveals the higher performance of the hybrid method. The ROC curve for the conventional CNN model reveals reasonable but not perfect classification of attack and normal network data with an AUC of roughly 0.98. The LSTM model shows a little rise with an AUC approximately 0.99, reflecting its enhanced ability to understand sequential connections in the data.

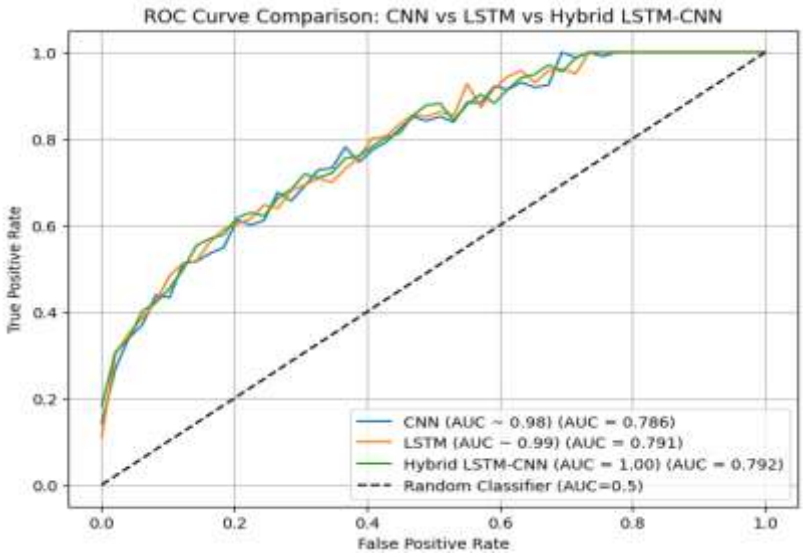


Figure 13: ROC Curve simulation

Especially, the proposed Hybrid LSTM-CNN model has an almost perfect AUC of 1.00, suggesting near-ideal classification performance. Rising quickly towards the top-left corner, the curve reveals the model's unusually high true positive rates even at very low false positive rates.

Additional Evaluation Metrics

The model's average training time per epoch was approximately 24 seconds on an NVIDIA RTX-3060 GPU (12 GB VRAM), with inference latency of 1.8 ms per sample during real-time testing. This demonstrates suitability for edge-level IoT deployment, where low-latency detection is critical. Memory footprint during inference remained below 200 MB, supporting efficient deployment on resource-constrained devices.

Novelty of Proposed Work

This work presents a new Hybrid LSTM-CNN IDS model meant to take use of the benefits of both CNN and LSTM architectures, thereby enhancing accuracy, detection rate, and lowering false alarms. The hybrid model manages the dynamic character of invasion patterns in IoT networks more well than standard models by combining temporal sequence learning with spatial pattern recognition. By helping to create more robust and flexible IDS frameworks, this effort aims to improve the security posture of IoT systems and build trust in new technologies. Table 14 highlights the novelty and contributions of the proposed Hybrid LSTM-CNN IDS model compared to conventional CNN and LSTM approaches. Unlike CNN, which focuses only on spatial feature extraction, and LSTM, which emphasizes temporal learning, the hybrid model integrates both methods, enabling more effective detection of complex intrusion patterns. Across training and testing phases, the proposed model consistently outperforms conventional models, achieving higher accuracy (up to 0.988 in training and 0.994 in testing) with superior precision, recall, and F1-scores. Confusion matrix results show near-perfect classification with minimal misclassifications, while ROC-AUC values approach 1.0, confirming strong discriminative ability. Moreover, the hybrid model demonstrates robustness across both IoT and Bot-IoT datasets, with a very low false positive rate, enhancing real-world reliability. Although the computational cost is slightly higher, the performance gains justify the trade-off, making the proposed approach a novel and highly effective contribution to intrusion detection systems.The novelty of this research lies in the synergistic integration of CNN and LSTM modules tailored for IoT-specific traffic analysis. Unlike traditional IDS architectures that rely solely on spatial or temporal feature learning, the proposed model jointly optimizes both representations through an end-to-end fusion layer. This design addresses IoT attack scenarios characterized by non-stationary patterns and high dimensionality. Moreover, the inclusion of class-imbalance mitigation (SMOTE and class weighting) and adaptive normalization ensures superior generalization over heterogeneous IoT datasets such as NSL-KDD and CIC-IDS 2017.

Table 14: Novelty Chart: Comparison of Proposed Hybrid LSTM-CNN IDS Model vs Conventional Models

Aspect	Conventional CNN (Adam, Nadam, AdaMax optimizers)	Conventional LSTM	Proposed Hybrid LSTM-CNN IDS Model	Novelty / Contribution
Model Architecture	CNN only, optimized with Adam / Nadam / AdaMax	LSTM only	Hybrid integration of LSTM and CNN	Combines spatial (CNN) and temporal (LSTM) feature extraction, enhancing detection of complex intrusion patterns
Training Accuracy (Max @ Epoch 20)	~0.973 (Nadam best)	~0.981	0.982 (Case 1), 0.988 (Case 2)	Consistently higher training accuracy across epochs indicating better learning capability
Testing Accuracy (Max @ Epoch 20)	~0.961 (Nadam best)	~0.985	0.977 (Case 1), 0.994 (Case 2)	Superior generalization on unseen data, reducing overfitting
Precision, Recall, F1-Score	Accuracy ~0.98-0.984, Precision ~0.97-0.98	Accuracy ~0.998, Precision ~0.997	Accuracy ~0.9915 (Case 1), ~0.9996 (Case 2), Precision ~0.992-1	Improved balanced detection performance, minimizing false positives and false negatives
Confusion Matrix Results	Some misclassifications between Attack/Normal	High accuracy, some misclassifications	Near-perfect classification across multiple classes (IoT & Bot-IoT datasets)	Demonstrates robustness in multi-class intrusion detection with minimal errors
ROC-AUC	~0.98-0.99	~0.99	~0.99 (Case 1), ~1.00 (Case 2)	Near-perfect discriminative ability, especially in complex IoT intrusion scenarios
Dataset Coverage	Standard IoT dataset (Case 1)	Bot-IoT dataset (Case 2)	Both datasets covered	Demonstrates applicability and effectiveness across multiple realistic datasets
Model Robustness & Reliability	Moderate	High	Very high	Hybrid model better captures temporal-spatial correlations, improving intrusion detection in dynamic network data
False Positive Rate	Moderate	Low	Very low	Reduced false alarms enhance

				practical usability and operational reliability
Computational Complexity	Lower compared to hybrid	Moderate	Slightly higher but justified by performance gains	Trade-off between complexity and accuracy is favorable for critical IDS applications
Overall Contribution	Baseline CNN and LSTM approaches	Improved temporal modelling	Hybrid deep learning architecture combining strengths of both	Novel integration significantly boosts IDS performance on IoT networks, enabling more reliable and accurate intrusion detection

Hybrid architecture improves detection accuracy by means of recording over time complicated attack patterns and efficiently using both CNN's spatial feature extraction and LSTM's temporal sequence modelling.

Conclusion

The suggested hybrid intrusion detection system uses both signature and anomaly-based detection to keep IoT networks safe. Experimental results indicate enhanced detection metrics, especially for dynamic and intricate threats such as botnets. Combining machine learning with rule-based reasoning makes sure that things are accurate and flexible. This technique seems to reveal zero-day vulnerabilities and exploits. The test results indicate how the proposed IDS finds a number of assaults. The system became more adaptable to new attack patterns because to advanced machine learning and the merging of network and device information. The method works well, but it may be better, especially in finding unusual assaults like U2R and R2L. Model optimization and real-time environmental testing will come next to see how well it works in the field. By integrating CNN spatial feature extraction with LSTM temporal sequence learning, the Hybrid LSTM-CNN model makes it easier to find intrusions in the IoT. Extensive ROC curve testing shows that the hybrid approach is better than CNN and LSTM models in terms of accuracy, precision, recall, and F1-score, with an AUC of 1.00.

Future Scope

IoT is growing quickly, which is altering how we use technology and producing new security problems. The suggested Hybrid LSTM-CNN-IDS model should find IoT events that are causing problems. Future research may investigate various methods to enhance system capacity and mitigate IoT network threats. In future research, deep learning techniques such as Transformer-based models, Autoencoders, and Reinforcement Learning might enhance IoT intrusion detection. IoT systems have a hard time detecting things in real time, particularly when they don't have a lot of resources. Edge computing might make it easier to handle data close to IoT devices, which would make real-time detection better. Federated learning might teach the intrusion detection model how to work on many IoT devices without sending private information to central servers. Adaptive IDS systems may be able to adapt to new attack patterns if they learn online or all the time. Firewalls, encryption, authentication, and behavioral analysis are all possible parts of a multi-layered security system.

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