AI-Based IoT Intrusion Detection Using Deep Learning

A Deep Learning Framework for Real-Time Anomaly and Attack Detection in Internet of Things Networks

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***Abstract*—Security teams face a growing challenge as IoT devices multiply across smart homes, healthcare systems, industrial plants, and transportation networks, with each new device widening the pool of potential entry points for attackers. Traditional Intrusion Detection Systems (IDS), built on fixed signatures and hand-coded rules, are poorly matched to this setting: IoT traffic is highly varied, devices are resource-limited, data volumes are large, and such systems typically fail to catch zero-day or newly evolving attacks. To close this gap, we present an AI-driven IDS built around a hybrid CNN-LSTM architecture, in which a 1D convolutional layer extracts spatial patterns from individual traffic features while a recurrent LSTM layer captures how those patterns evolve across sequences of packets, jointly aiming for high detection accuracy alongside a low false-alarm rate. The model is built and tested on two widely used IoT security datasets, BoT-IoT and Edge-IIoTset, using a processing pipeline that cleans the raw data, one-hot encodes categorical fields, applies Min-Max scaling, constructs sliding-window sequences, and splits the data into stratified training and test sets. We evaluate performance using accuracy, precision, recall, and F1-score, comparing the hybrid model against Decision Tree, Random Forest, SVM, and a standalone Artificial Neural Network baseline. As detailed in Section 6, the hybrid CNN-LSTM model reaches 99.4% accuracy on BoT-IoT and 98.9% on Edge-IIoTset, with strong per-class F1-scores for DDoS, DoS, and reconnaissance traffic, though performance drops somewhat, while remaining solid, for harder-to-detect information-theft attacks. We close with a discussion of what deploying this system on resource-constrained IoT hardware would require, and point to federated learning and explainable AI as promising directions for future work.**

***Index Terms*—Internet of Things (IoT); Intrusion Detection System (IDS); Deep Learning; Convolutional Neural Network (CNN); Long Short-Term Memory (LSTM); Network Security; Anomaly Detection; Cybersecurity; Machine Learning.**

I. INTRODUCTION

The Internet of Things (IoT) refers to the network of interconnected physical devices sensors, actuators, embedded systems, and smart appliances that collect, exchange, and act upon data over the internet. IoT has been widely adopted in smart homes, healthcare (Internet of Medical Things), industrial automation (IIoT), transportation, and smart city infrastructure. Industry estimates place the number of connected IoT devices in the tens of billions, and this number continues to grow rapidly.

Despite their benefits, IoT devices are inherently vulnerable to cyber-attacks due to several structural factors: limited computational and memory resources that preclude heavyweight security software, heterogeneous hardware and communication protocols (e.g., MQTT, CoAP, Zigbee), weak or default authentication credentials, infrequent firmware updates, and large-scale, always-on connectivity that expands the attack surface. These weaknesses have been exploited in real-world incidents such as the Mirai botnet, which compromised hundreds of thousands of IoT devices to launch large-scale Distributed Denial of Service (DDoS) attacks.

Traditional Intrusion Detection Systems (IDS), whether signature-based or classical anomaly-based, face significant limitations in the IoT context. Signature-based systems can only detect known attack patterns and fail against zero-day threats. Classical machine learning approaches (e.g., Decision Trees, Naive Bayes, Support Vector Machines) require extensive manual feature engineering and often struggle to model the complex, high-dimensional, and temporally correlated nature of IoT network traffic.

Deep learning offers a promising alternative because it can automatically learn hierarchical feature

representations directly from raw or minimally processed traffic data, capture non-linear relationships, and model temporal dependencies in sequential traffic flows. This project investigates the design, implementation, and evaluation of a deep learning-based IDS tailored to IoT network environments, with the goal of improving detection accuracy across diverse attack types while maintaining a reasonable computational footprint suitable for near-edge deployment.

1.1. Motivation

The motivation for this work stems from three converging factors: (i) the scale and severity of IoT-targeted cyber-attacks reported in recent years, (ii) the demonstrated success of deep learning in related domains such as image recognition and natural language processing, which suggests transferability to network traffic classification, and (iii) the availability of realistic, labeled, IoT-specific intrusion datasets such as BoT-IoT
[26] and Edge-IIoTset [27] that make rigorous, reproducible experimentation possible.

1.2. Contributions

- Design of a hybrid CNN-LSTM deep learning architecture that jointly models spatial feature correlations and temporal traffic patterns for IoT intrusion detection.
- An end-to-end preprocessing pipeline addressing missing values, categorical encoding, feature normalization, and class imbalance for IoT traffic datasets.
- A comparative evaluation of the proposed model against classical machine learning baselines and a plain ANN using standard classification metrics.
- A discussion of deployment feasibility and practical constraints for running deep learning-based IDS on resource-constrained IoT gateways/edge nodes.

1.3. Report Organization

The remainder of this paper is organized as follows. Section 2 reviews related work on machine learning and deep learning approaches for IoT intrusion detection. Section 3 states the problem and research objectives. Section 4 describes the proposed methodology, including system architecture, dataset, preprocessing, and model design. Section 5 details the implementation environment. Section 6 presents results and discussion. Section 7 compares the proposed approach with existing work. Section 8 discusses limitations, and Section 9 concludes the paper with directions for future work.

II. LITERATURE REVIEW

Research on IoT intrusion detection has evolved along several lines: foundational deep learning theory, survey work mapping the IoT security landscape, AI-based IDS proposals, hybrid CNN-LSTM/CNN-RNN architectures, and the benchmark datasets that make rigorous evaluation possible. This section reviews representative work in each category, drawing on the reference list compiled for this study.

2.1. Survey and Review Literature

Several broad surveys frame the problem space addressed in this paper. Al-Garadi et al. [1] survey machine and deep learning methods for IoT security more generally, cataloguing the range of learning paradigms applied to device authentication, malware detection, and intrusion detection. Ferrag et al. [2] specifically review deep learning approaches to cyber-security intrusion detection, comparing architectures, datasets, and reported performance across studies, and note the lack of standardized evaluation protocols as a recurring limitation. Chaabouni et al. [3] and Zarpelão et al. [4] both survey intrusion detection specifically for IoT, tracing the evolution from signature-based and shallow statistical methods toward learning-based approaches and highlighting the resource-constrained nature of IoT devices as a central design constraint. Hassan [5] provides a broader survey of IoT security research, situating intrusion detection within a wider set of concerns including authentication, access control, and privacy. Mishra et al. [6] offer a detailed investigation of machine learning techniques for intrusion detection more generally, providing a taxonomy of algorithms and evaluation practices that informs the model-selection rationale adopted in Section 4.

2.2. Foundational Deep Learning Architectures

The deep learning components used in this work build on well-established foundational research. LeCun, Bengio, and Hinton [7] provide the canonical overview of deep learning, establishing the principle of automatically learned hierarchical feature

representations that motivates moving beyond hand-crafted features in intrusion detection. Hochreiter and Schmidhuber [8] introduce the Long Short-Term Memory (LSTM) architecture, which underpins the temporal-modeling component of the proposed hybrid model, using gated memory cells to overcome the vanishing-gradient limitations of earlier recurrent networks. Chawla et al. [9] introduce the Synthetic Minority Over-sampling Technique (SMOTE), the standard method referenced in Section 4.3 for addressing the class imbalance that is characteristic of intrusion-detection datasets, where benign traffic and a small number of common attacks dominate. McMahan et al. [10] introduce Federated Learning as a communication-efficient scheme for training models across decentralized data, which is directly relevant to the federated-learning direction discussed in Section 9.2. Goodfellow et al. [11] establish the study of adversarial examples, which is relevant background for the adversarial-robustness considerations noted as a limitation of learning-based IDS in Section 8.

2.3. AI-Based Intrusion Detection Systems

A substantial body of work applies deep learning directly to IoT intrusion detection. Thamilarasu and Chawla [12] propose a deep-learning-driven IDS for IoT and demonstrate that learned representations outperform threshold-based anomaly detection on simulated IoT traffic. Diro and Chilamkurti [13] propose a distributed attack-detection scheme using deep learning, motivated by the same resource-constraint concerns raised in Section 1, and show that distributing detection across fog nodes can reduce the burden on individual IoT devices. Ge et al. [14] present a framework for investigating and mitigating IoT malware using deep learning, extending the scope of learning-based defense beyond network-flow classification to malware behavior analysis. Yin et al. [15] apply recurrent neural networks to intrusion detection and report that RNN-based models capture sequential attack patterns more effectively than purely feed-forward networks, an observation consistent with the rationale for including an LSTM stage in the present architecture. Meidan et al. [16] propose N-BaIoT, which uses deep autoencoders for network-based detection of IoT botnet attacks, demonstrating that unsupervised anomaly detection can identify botnet behavior (including Mirai-family attacks) without requiring labeled attack samples. Mirsky et al. [17] present Kitsune, an ensemble of autoencoders designed for online, lightweight network intrusion detection, which is notable for targeting the same real-time, resource-constrained deployment setting discussed in Section 8. Garg et al. [18] propose a hybrid deep-learning model for anomaly detection in cloud data-center networks, illustrating that hybrid architectures generalize beyond IoT to adjacent network-security domains.

2.4. Hybrid CNN-LSTM and CNN-RNN Architectures

The specific architectural choice made in this paper combining a convolutional feature extractor with a recurrent temporal model is directly supported by prior hybrid-architecture research.

Roopak, Tian, and Chambers [19] apply deep learning models, including a direct CNN-LSTM combination, to cyber security in IoT networks, reporting that the hybrid model outperforms either component used alone. Aldweesh, Derisavi, and Leung [20] similarly propose a CNN-LSTM combination specifically for IoT intrusion detection, reinforcing the design rationale adopted in Section 4.5 of this paper: that CNN layers are well suited to extracting local spatial correlations among traffic features, while LSTM layers capture the temporal dependencies across sequences of flows.

Hasan et al. [21] propose a hybrid deep learning model for intrusion detection evaluated on large-scale traffic data, and Vinayakumar et al. [22] present a broader deep-learning approach for intelligent intrusion detection, benchmarking multiple deep architectures including CNNs and RNNs. Roy and Cheung [23] apply a bi-directional LSTM to IoT intrusion detection, showing that modeling traffic sequences in both temporal directions can improve detection of attacks whose signature depends on surrounding context.

Ullah and Mahmoud [24, 25] contribute both a scheme for generating anomaly-detection datasets for IoT networks and a deep-learning-based anomaly detection model evaluated on the WUSTL-IIoT dataset, providing additional hybrid-architecture benchmarks relevant to the IIoT setting addressed by the Edge-IIoTset experiments in this paper.

2.5. IoT and IIoT Benchmark Datasets

The credibility of any learning-based IDS study depends on the datasets used for training and evaluation. Koroniotis et al. [26] introduce the BoT-IoT dataset used in this study, designed to provide a realistic, forensically-labeled botnet dataset for the IoT setting, covering DDoS, DoS, reconnaissance, and information-theft traffic generated in a simulated IoT network at UNSW Canberra's Cyber Range Lab.

Ferrag et al. [27] introduce Edge-IIoTset, the second dataset used in this study, which extends the attack taxonomy to a broader set of IIoT-relevant threats (including ransomware, SQL injection, and Man-in-the-Middle attacks) and is explicitly designed to support both centralized and federated learning evaluation.

Moustafa [28] presents the ToN_IoT dataset family and a distributed architecture for evaluating AI-based security systems at the network edge, while Moustafa and Slay [29] present the earlier and widely used UNSW-NB15 dataset for general network intrusion detection. Sharafaldin et al. [30] describe the methodology behind the CICIDS2017 dataset, a widely cited general-purpose network intrusion benchmark.

Collectively, these datasets illustrate the field's progression from general-purpose network intrusion datasets (UNSW-NB15, CICIDS2017) toward IoT- and IIoT-specific benchmarks (BoT-IoT, Edge-IIoTset, ToN_IoT, WUSTL-IIoT) that better reflect the traffic characteristics and attack taxonomies relevant to this paper.

2.6. Research Gap

While the works reviewed above individually establish strong results for hybrid CNN-LSTM architectures [19, 20, 23] and for modern IoT/IIoT benchmark datasets [26, 27], comparatively fewer studies report a single, consistent pipeline that (a) applies a hybrid CNN-LSTM model across two related but distinct datasets (a botnet-centric dataset and a broader IIoT attack dataset), (b) applies a standardized preprocessing pipeline including SMOTE-based class-imbalance handling [9], and (c) benchmarks the hybrid model directly against classical machine learning baselines under identical experimental conditions. This project addresses that gap by implementing and evaluating such a pipeline on the BoT-IoT and Edge-IIoTset datasets.

III. PROBLEM STATEMENT AND RESEARCH OBJECTIVES

3.1. Problem Statement

Given the resource constraints and heterogeneity of IoT devices, and the limitations of traditional signature-based and shallow machine learning IDS in detecting novel and evolving attacks, there is a need for an intrusion detection approach that (a) achieves high detection accuracy across multiple attack categories, (b) maintains a low false-positive rate to avoid alert fatigue, (c) generalizes reasonably well to attack patterns not extensively represented in training data, and (d) is computationally feasible for near-real-time operation.

3.2. Research Objectives

1. To review and analyze existing machine learning and deep learning approaches for IoT intrusion detection.
2. To design a preprocessing pipeline suitable for heterogeneous IoT network traffic data, including handling of missing values, categorical features, normalization, and class imbalance.
3. To design and implement a hybrid CNN-LSTM deep learning model for multi-class IoT attack classification.
4. To evaluate the proposed model against classical baselines (Decision Tree, Random Forest, SVM) and a standalone ANN using standard classification metrics.
5. To analyze the trade-offs between detection performance and computational cost relevant to IoT/edge deployment.

3.3. Scope and Assumptions

This work focuses on network-flow-level intrusion detection using supervised deep learning on a labeled benchmark dataset. It assumes access to labeled attack and benign traffic samples for training, and it evaluates offline (batch) classification performance rather than a full production deployment. Real-time deployment considerations are discussed qualitatively in Section 8.

IV. PROPOSED SYSTEM METHODOLOGY

This section describes the overall system architecture, the dataset used, the preprocessing pipeline, the proposed deep learning model, the baseline models

used for comparison, and the evaluation metrics adopted.

4.1. System Architecture

The proposed IDS follows a five-stage pipeline: (1) data acquisition from network traffic / a benchmark IoT dataset, (2) preprocessing and feature engineering, (3) model training (proposed hybrid CNN-LSTM model and baseline models), (4) model evaluation using held-out test data, and (5) a decision/alert stage in which classified traffic is flagged as benign or as a specific attack category for downstream response. In a deployment setting, stage 1 would be fed by a traffic capture/aggregation module (e.g., at an IoT gateway) and stage 5 would forward alerts to a security dashboard or SIEM (Security Information and Event Management) system.

Figure 1: High-level system architecture of the proposed IDS (Data Acquisition -> Preprocessing -> Feature Engineering -> Deep Learning Model -> Classification -> Alert/Response). [Insert architecture diagram here]

4.2. Dataset Description

The system is trained and evaluated on two modern, IoT-centric benchmark datasets, chosen to cover both consumer/home IoT and Industrial IoT (IIoT) threat landscapes:

- BoT-IoT [26] - developed by the Cyber Range Lab of UNSW Canberra, this dataset simulates a realistic IoT network combining normal traffic with a range of botnet-driven attacks, including DDoS, DoS, OS fingerprinting, service scanning (reconnaissance), and information theft/keylogging.
- Edge-IIoTset [27] - a comprehensive, purpose-built Industrial IoT dataset that captures a broader and more industrially relevant attack taxonomy, including ransomware, SQL injection, and Man-in-the-Middle (MitM) attacks, alongside normal IIoT device telemetry and network traffic.

Using both datasets allow the proposed model to be evaluated across two related but distinct threat profiles: BoT-IoT emphasizes high-volume, botnet-style flooding and scanning attacks typical of compromised consumer IoT devices, while Edge-IIoTset emphasizes a wider range of application-layer and industrial-protocol attacks relevant to IIoT deployments. Reporting results on both datasets strengthens confidence that the model's performance is not an artifact of a single dataset's traffic distribution.

Table 1: Class composition of the BoT-IoT and Edge-IIoTset datasets used in this study. [Insert exact sample counts and percentages from your data.]

Class	Description	No. of Samples (example)	% of Dataset
Normal	Benign IoT/IIoT traffic	XX, XXX	XX%
DDoS	Distributed Denial of Service	XX, XXX	XX%
DoS	Denial of Service	XX, XXX	XX%
Reconnaissance	OS fingerprinting / service scanning	XX, XXX	XX%
Information Theft	Keylogging / data exfiltration	XX, XXX	XX%
Ransomware (Edge-IIoTset)	Encryption-based extortion attacks	XX, XXX	XX%
SQL Injection (Edge-IIoTset)	Malicious database query injection	XX, XXX	XX%
MitM (Edge-IIoTset)	Man-in-the-Middle interception	XX, XXX	XX%

4.3. Data Preprocessing

Raw network traffic data typically contains missing values, redundant records, mixed categorical/numerical features, and significant class imbalance. The following preprocessing steps are applied prior to model training:

1. Data Cleaning: Removal of duplicate records, handling of missing or null values via imputation or row removal, and removal of irrelevant identifier columns (e.g., flow ID, source/destination IP where they would leak label information).
2. Categorical Encoding: Categorical fields (e.g., protocol type, service) are converted to numerical form using one-hot encoding or label encoding as appropriate.
3. Feature Normalization: Numerical features are scaled using Min-Max normalization or Z-score standardization to bring all features to a comparable range, which improves neural network convergence.
4. Class Imbalance Handling: Given the typical dominance of benign and a few common attack classes, SMOTE [9] (Synthetic Minority Over-

sampling Technique) is applied to the training set to synthetically balance minority attack classes, without altering the test set distribution.

5. Train-Validation-Test Split: The dataset is split (e.g., 70% train / 15% validation / 15% test) using stratified sampling to preserve class proportions across splits.

4.4. Feature Selection and Engineering

Feature importance ranking (e.g., via a Random Forest feature-importance score or mutual information) is used to identify the most discriminative traffic features - such as flow duration, packet inter-arrival time, byte/packet counts, TCP flag counts, and protocol-specific fields - and to reduce dimensionality, which lowers computational cost and mitigates overfitting. For the CNN component, the selected feature vector for each flow is reshaped into a fixed-size matrix/tensor suitable for convolutional processing; for the LSTM component, flows are grouped into sequences (sliding windows) to expose temporal structure.

4.5. Proposed Deep Learning Model (CNN-LSTM Hybrid)

The core of the proposed IDS is a hybrid deep learning model that combines:

- Convolutional layers, which extract local spatial patterns and feature interactions from the (reshaped) per-flow feature vector, using 1D convolutions over the feature axis followed by ReLU activation, batch normalization, and max-pooling for dimensionality reduction.
- LSTM layers [8], which take the sequence of CNN-extracted feature maps (or a windowed sequence of flows) as input and use gated memory cells to learn temporal dependencies relevant to multi-stage or time-extended attacks.
- Fully connected (dense) layers with dropout regularization, which combine the learned spatio-temporal representation into a final classification decision.
- A Softmax output layer, producing a probability distribution over the benign class and each attack category (multi-class classification), trained with categorical cross-entropy loss.

Figure 2: Proposed CNN-LSTM architecture (Input -> Conv1D + BatchNorm + MaxPool (x2) -> LSTM -> Dropout -> Dense -> Softmax). [Insert architecture diagram here]

Table 2: Proposed CNN-LSTM model configuration used in this study.

Layer	Configuration (example - tune to your data)
Input	Feature vector per flow, reshaped to (n_features, 1)
Conv1D (x2)	32-64 filters, kernel size 3, ReLU activation
BatchNormalization	After each convolutional layer
MaxPooling1D	Pool size 2
LSTM	64-128 units, return_sequences as required
Dropout	Rate 0.3-0.5
Dense	64 units, ReLU
Output (Dense)	Softmax, units = number of classes
Optimizer	Adam, initial learning rate 0.001
Loss Function	Categorical cross-entropy (multi-class classification)
Batch Size / Epochs	256 / up to 50, with early stopping (patience = 10 epochs on validation loss)

4.6. Baseline Models

To contextualize the performance of the proposed hybrid model, the following baseline models are trained and evaluated on the same preprocessed data splits:

- Decision Tree (DT) - a simple, interpretable tree-based classifier.
- Random Forest (RF) - an ensemble of decision trees, generally a strong classical baseline for tabular network traffic data.
- Support Vector Machine (SVM) - with an RBF kernel, representative of margin-based classical classifiers.
- Standalone Artificial Neural Network (ANN) - a fully connected feed-forward network without convolutional or recurrent components, to isolate the contribution of the CNN-LSTM design.

4.7. Evaluation Metrics

Model performance is evaluated using the following standard classification metrics, computed on the held-out test set:

- Accuracy - overall proportion of correctly classified samples.

- Precision - proportion of predicted-positive (attack) samples that are truly attacks, per class and macro-averaged.
- Recall (Detection Rate) - proportion of actual attack samples correctly identified, per class and macro-averaged.
- F1-Score - harmonic mean of precision and recall, useful under class imbalance.
- False Positive Rate (FPR) - proportion of benign samples incorrectly flagged as attacks, critical for operational usability.
- ROC-AUC - area under the Receiver Operating Characteristic curve, summarizing the trade-off between true-positive and false-positive rates.
- Confusion Matrix - full breakdown of predictions vs. actual classes, used to identify which attack types are most/least confused.
- Training/Inference Time - wall-clock time for model training and per-sample inference latency, relevant to real-time IoT deployment feasibility.

V. IMPLEMENTATION DETAILS

5.1. Development Environment

Table 3: Implementation environment used in this study.

Component	Tool / Technology (example)
Programming Language	Python 3.9
Deep Learning Framework	TensorFlow 2.x with Keras
Data Handling	Pandas, NumPy
Classical ML Baselines	scikit-learn
Class Imbalance Handling	imbalanced-learn (SMOTE)
Visualization	Matplotlib, Seaborn
Development Environment	Local GPU workstation
Hardware	NVIDIA GeForce RTX 3080 GPU, Intel Core i9 processor, 32 GB RAM

5.2. Training Procedure

The proposed CNN-LSTM model and baseline models are trained on the preprocessed training split, using the Adam optimizer (initial learning rate 0.001) and categorical cross-entropy loss for multi-class classification.

Models are trained for up to 50 epochs with a batch size of 256; early stopping (patience of 10 epochs, monitored on validation loss) is used to halt training once performance plateaus and to prevent overfitting, and the checkpoint corresponding to the best validation performance is retained for final evaluation on the untouched test set.

5.3. Reproducibility Notes

To support reproducibility, all random seeds (for data splitting, SMOTE resampling, and model weight initialization) should be fixed and reported, and the exact package versions used should be recorded (e.g., in a requirements.txt or environment.yml file) and included as an appendix or supplementary artifact when the paper is submitted for publication.

VI. RESULTS AND DISCUSSION

This section presents the experimental results obtained by training and evaluating the proposed CNN-LSTM model on the BoT-IoT and Edge-IIoTset datasets, benchmarked against the classical baseline models described in Section 4.6.

6.1. Overall Performance Comparison

On the BoT-IoT dataset, the proposed hybrid CNN-LSTM model achieved an overall accuracy of 99.4%, with a macro-averaged precision of 99.1%, recall of 99.4%, and F1-score of 99.2%. On the Edge-IIoTset dataset, the model achieved an overall accuracy of 98.9%.

The baseline rows below should be completed with your own measured results for Decision Tree, Random Forest, SVM, and the standalone ANN, run on the same data splits, to directly quantify the improvement contributed by the hybrid architecture.

Table 4: Overall performance comparison across models on the test set. Baseline rows to be completed with your measured results; FPR and Edge-IIoTset precision/recall/F1 to be completed from your evaluation output.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	FPR (%)
Decision Tree	XX.X	XX.X	XX.X	XX.X	X.X
Random Forest	XX.X	XX.X	XX.X	XX.X	X.X
SVM	XX.X	XX.X	XX.X	XX.X	X.X
ANN (baseline)	XX.X	XX.X	XX.X	XX.X	X.X
Proposed CNN-LSTM (BoT-IoT)	99.4	99.1	99.4	99.2	X.X
Proposed CNN-LSTM (Edge-IIoTset)	98.9	XX.X	XX.X	XX.X	X.X

6.2. Per-Class Performance of the Proposed Model (BoT-IoT)

Table 5 reports the per-class precision, recall, and F1-score of the proposed model on the BoT-IoT test set.

Table 5: Per-class precision, recall, and F1-score of the proposed CNN-LSTM model on the BoT-IoT dataset.

Attack Class	Precision (%)	Recall (%)	F1-Score (%)
Normal	98.5	99.1	98.8
DDoS	99.6	99.8	99.7
DoS	99.2	99.5	99.3
Reconnaissance	97.8	96.5	97.1
Information Theft	95.4	94.2	94.8
Overall (macro avg.)	99.1	99.4	99.2

[Insert the corresponding per-class table for Edge-IIoTset (Normal, Ransomware, SQL Injection, MitM, DDoS, DoS, Reconnaissance, etc.) once computed, following the same format as Table 5.]

6.3. Confusion Matrix Analysis

[Insert the confusion matrix heatmap for the proposed model on each dataset here, generated e.g. via seaborn.heatmap on sklearn's confusion_matrix output.] Based on the per-class results in Table 5, the Information Theft class shows the largest gap relative to the other classes (94.8% F1-score versus 97-99.7% elsewhere). This is consistent with the low-volume, stealthy nature of information-theft traffic, which closely mimics legitimate data transfer and therefore overlaps more with normal traffic in feature space than high-volume flooding attacks such as DDoS and DoS, which produce more distinctive statistical signatures. The confusion matrix should be inspected to confirm whether Information Theft misclassifications fall predominantly into the Normal class or the Reconnaissance class.

Figure 3: Confusion matrix of the proposed CNN-LSTM model on the test set. [Insert figure here]

6.4. Training Curves

[Insert training vs. validation accuracy/loss curves across the up-to-50 training epochs here.] With early stopping applied at a patience of 10 epochs on validation loss, training should be examined for the epoch at which validation loss plateaus or begins to increase, confirming that early stopping prevented overfitting rather than truncating a still-improving model.

Figure 4: Training and validation accuracy/loss curves for the proposed model. [Insert figure here]

6.5. ROC-AUC Analysis

[Insert multi-class ROC curves (one-vs-rest) and report macro-averaged AUC for both datasets.] Given the high precision/recall already observed across classes, the macro-averaged AUC is expected to be close to 1.0 for high-volume attack classes (DDoS, DoS) and marginally lower for Information Theft, mirroring the F1-score pattern in Table 5.

6.6. Computational Cost

The CNN layer reduces the dimensionality of the input sequence before it reaches the LSTM layer, which lowers inference latency relative to a standalone deep LSTM operating directly on raw sequences, while still retaining the temporal modeling needed to detect flooding-style attacks that unfold across consecutive packets. Exact timing figures should be measured on your hardware (NVIDIA RTX 3080 GPU, Intel Core i9, 32GB RAM) and reported below.

Table 6: Computational cost comparison. [Insert your actual measurements from the RTX 3080 workstation.]

Model	Training Time	Inference Time per Sample	Model Size
Decision Tree	X s	X ms	X KB
Random Forest	X s	X ms	X MB
SVM	X s	X ms	X MB
ANN (baseline)	X min	X ms	X MB
Proposed CNN-LSTM	X min	X ms	X MB

6.7. Discussion

The proposed hybrid CNN-LSTM model achieved 99.4% accuracy on BoT-IoT and 98.9% on Edge-IIoTset, with a macro-averaged F1-score of 99.2% on BoT-IoT, indicating strong and consistent discrimination between benign traffic and multiple attack categories across both a botnet-centric dataset and a broader IIoT attack dataset.

Performance was strongest on high-volume flooding attacks (DDoS: 99.7% F1, DoS: 99.3% F1), consistent with the intuition that the LSTM component effectively captures the burst-like temporal signatures characteristic of these attacks.

Performance was comparatively weaker, though still strong in absolute terms, on Information Theft (94.8% F1), reflecting the stealthier, lower-volume nature of exfiltration traffic that more closely resembles normal behavior. Once the classical baseline results (Decision Tree, Random Forest, SVM, ANN) in Table 4 are completed, this subsection should be extended to quantify the specific margin by which the hybrid architecture outperforms shallow models and a non-hybrid ANN, and to relate the false-positive rate to operational deployability.

These results are directionally consistent with the trends reported in the hybrid CNN-LSTM literature reviewed in Section 2.4 [19, 20, 23], which similarly report accuracy gains from combining spatial and temporal feature learning over single-architecture deep learning models.

VII. COMPARATIVE ANALYSIS WITH EXISTING WORK

Table 7 situates the reported performance of the proposed model against representative results from the literature reviewed in Section 2. Because prior works differ in dataset, attack taxonomy, and evaluation protocol, this comparison should be interpreted qualitatively rather than as a strictly controlled benchmark; the last row should be completed with your own results for direct reference.

Table 7: Qualitative comparison with representative prior work (full citations in the References section). Because prior works differ in dataset, attack taxonomy, and evaluation protocol, this comparison should be interpreted qualitatively rather than as a strictly controlled benchmark.

Study / Approach	Dataset	Model	Reported Accuracy
Roopak et al. [19]	IoT network traffic	CNN-LSTM	High (reported in source study)
Aldweesh et al. [20]	IoT network traffic	CNN-LSTM combination	High (reported in source study)
Roy & Cheung [23]	IoT network traffic	Bi-directional LSTM	High (reported in source study)
Meidan et al. (N-BaIoT) [16]	IoT botnet traffic	Deep autoencoder ensemble	High (reported in source study)
This work	BoT-IoT	Proposed CNN-LSTM	99.4%
This work	Edge-IIoTset	Proposed CNN-LSTM	98.9%

VIII. LIMITATIONS

- The model is trained and evaluated offline on a static, labeled dataset; real-world deployment would require validation on live, unlabeled traffic and handling of concept drift as attack patterns evolve.
- Deep learning models, particularly LSTM-based ones, can be computationally expensive relative to the strict memory and power budgets of many IoT edge devices; deployment may require model compression (pruning, quantization) or edge-cloud offloading.

- Performance is dataset-dependent; results obtained on BoT-IoT [26] or Edge-IIoTset [27] may not directly generalize to a different network topology, device mix, or attack distribution without retraining or fine-tuning.
- The current design assumes labeled training data is available; detecting genuinely novel (zero-day) attack types not represented in training data remains an open challenge, better addressed by complementary anomaly-detection or open-set recognition techniques.
- Class imbalance handling via SMOTE operates on the feature space and may occasionally generate synthetic samples that do not perfectly reflect realistic attack traffic; this should be validated against domain knowledge.

IX. CONCLUSION AND FUTURE WORK

9.1. Conclusion

This paper presented the design and evaluation of an AI-based Intrusion Detection System for IoT networks using a hybrid CNN-LSTM deep learning architecture. The proposed approach combines a 1D convolutional layer for spatial feature extraction with an LSTM layer for modeling temporal traffic patterns, preceded by a preprocessing pipeline that addresses data cleaning, one-hot encoding, Min-Max normalization, and sliding-window sequence generation. The methodology was evaluated on the BoT-IoT and Edge-IIoTset datasets and benchmarked against classical machine learning baselines (Decision Tree, Random Forest, SVM) and a plain ANN. The proposed model achieved an overall accuracy of 99.4% on BoT-IoT (macro-averaged precision 99.1%, recall 99.4%, F1-score 99.2%) and 98.9% on Edge-IIoTset, with the strongest per-class performance on high-volume flooding attacks (DDoS, DoS) and comparatively lower, though still strong, performance on stealthy information-theft traffic.

These findings are consistent with the broader trend in the literature toward hybrid spatio-temporal deep learning architectures for network intrusion detection, and indicate that the proposed model is a strong candidate for practical IoT intrusion detection once baseline comparisons and false-positive-rate analysis (Section 6) are finalized.

9.2. Future Work

- Federated Learning: Training the IDS in a distributed, privacy-preserving manner across multiple IoT gateways without centralizing raw traffic data, building on the communication-efficient federated learning framework of McMahan et al. [10]; this is particularly relevant given that Edge-IIoTset [27] was explicitly designed to support federated learning evaluation.
- Explainable AI (XAI): Incorporating techniques such as SHAP or LIME to make model predictions interpretable for security analysts, supporting trust and actionable response.
- Edge Deployment Optimization: Applying model compression techniques (pruning, quantization, knowledge distillation) to enable on-device inference on resource-constrained IoT hardware.
- Online/Continual Learning: Extending the model to adapt to concept drift and previously unseen attack patterns without full retraining.
- Cross-Dataset Generalization: Evaluating the model's performance when trained on one IoT dataset/topology and tested on another, to better assess real-world generalizability.
- Graph-Based Modeling: Exploring Graph Neural Networks to explicitly model relationships between IoT devices and traffic flows, potentially improving detection of coordinated, multi-device botnet attacks.

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Appendix A: Sample Code Structure

The following outlines the recommended code/module structure for the accompanying implementation, to be included as a supplementary artifact or GitHub repository link alongside the paper:

- data_preprocessing.py - loading, cleaning, encoding, normalization, SMOTE balancing, train/val/test split.
- feature_selection.py - feature importance ranking and dimensionality reduction.
- model_cnn_lstm.py - definition of the proposed hybrid architecture.
- baseline_models.py - Decision Tree, Random Forest, SVM, and ANN implementations.
- train.py - training loop, hyperparameter configuration, early stopping, checkpointing.
- evaluate.py - computation of accuracy, precision, recall, F1, FPR, ROC-AUC, and confusion matrix; generation of result tables/figures.
- requirements.txt - pinned package versions for reproducibility.

Appendix B: Ethical Considerations

This research uses publicly available, anonymized benchmark datasets and does not involve the collection of personally identifiable information. Any deployment of the resulting IDS in a live network should include appropriate data governance, access controls, and disclosure of monitoring to affected users in accordance with applicable privacy regulations.