MANTECH Publications

Journal of Internet of Things and Information Technology
Volume 8, Issue 3, September-December, 2025
ISSN: 3107-4502 (Online)

Intrusion Detection System for Iot Devices Using CNN-LSTM Based Hybrid Framework

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ABSTRACT

The proliferation of Internet of Things (IoT) devices has significantly expanded the attack surface for cybercriminals, necessitating robust intrusion detection systems (IDS). Traditional machine learning-based IDS often struggle with adaptability, scalability, and detection of sophisticated attacks. This paper proposes a hybrid deep learning model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for IoT intrusion detection. The CNN extracts spatial traffic features, while the LSTM captures temporal dependencies. Extensive experiments were conducted on NSL-KDD, benchmarking the hybrid CNN-LSTM model against standalone CNN, LSTM methods. These findings highlight the feasibility of deploying hybrid deep learning IDS on resource-constrained IoT edge devices.

KEYWORDS: - *IoT Security, Intrusion Detection System, Deep Learning, CNN-LSTM, Adversarial Robustness, Edge Computing*

INTRODUCTION

The Internet of Things (IoT) has grown into a global ecosystem interconnecting billions of devices in diverse domains, including healthcare, industrial automation, smart homes, and transportation. The number of connected devices is expected to reach tens of billions by the end of this decade, generating vast amounts of heterogeneous network traffic. While this connectivity improves efficiency and enables new services, it also significantly expands the

attack surface for cybercriminals. Attacks such as Distributed Denial of Service (DDoS), botnets, data exfiltration, and privilege escalation targeting IoT devices have surged in recent years, with botnet-based threats like Mirai demonstrating the devastating impact of compromised IoT infrastructure [12], [13].

Traditional intrusion detection systems (IDS), particularly signature-based methods, are limited in handling the dynamic, high-dimensional, and evolving nature of IoT traffic. These systems are often unable to detect zero-day or polymorphic attacks and struggle with scalability when applied to large-scale IoT networks [11]. To overcome these limitations, researchers have increasingly turned to machine learning (ML) and, more recently, deep learning (DL)-based approaches [1]–[4].

Deep learning IDS have demonstrated strong capabilities in capturing complex patterns from network traffic. CNNs are effective in extracting local spatial features from flow records, while LSTMs are adept at modeling sequential dependencies, making them well-suited for temporal traffic analysis [2], [3]. However, standalone CNN or LSTM models often fail to capture the full complexity of IoT traffic patterns. Recent studies propose hybrid CNN-LSTM architectures that leverage both spatial and temporal feature learning to achieve superior detection accuracy [1], [2], [4], [5]. These hybrid models have shown strong results in multi-class classification tasks and are especially useful for detecting rare but critical intrusion types such as R2L and U2R. Despite these advancements, three important challenges remain unaddressed in much of the literature:

1. **Adversarial Robustness** – DL-based IDS models are vulnerable to adversarial perturbations. Techniques such as the Fast Gradient Sign Method (FGSM) [6] can reduce detection accuracy drastically. Although recent works emphasize the need for adversarial testing [7], many hybrid IDS studies still overlook this dimension.
2. **Resource Constraints** – IoT devices are inherently resource-limited. While CNN-LSTM models achieve high accuracy, they can be computationally expensive. Lightweight IDS methods such as TinyML [8] and model compression have been proposed, but few works systematically evaluate hybrid models on edge hardware like Raspberry Pi or Jetson Nano.
3. **Privacy and Scalability** – With IoT devices distributed globally, centralized IDS training can raise privacy risks and scalability challenges. Federated learning (FL) has emerged as a promising paradigm to train IDS collaboratively without sharing raw data [9], [10], yet

its integration with hybrid CNN-LSTM models remains underexplored.

By combining accuracy, adversarial robustness, and deployment feasibility, this work advances the state of IoT intrusion detection and lays the foundation for future lightweight and distributed IDS frameworks.

RELATED WORK

Intrusion detection for IoT networks has received increasing attention in recent years. Existing works can be broadly grouped into deep learning-based IDS approaches, adversarial robustness studies, lightweight IDS for edge computing, and federated/distributed learning for IoT security.

1. Deep Learning Approaches (CNN, LSTM, and Hybrids)

CNN and LSTM architectures have been widely applied to IDS because they capture complementary traffic characteristics. CNNs extract local/spatial patterns, while LSTMs capture sequential dependencies across flows. Hybrid CNN-LSTM approaches often outperform single-architecture models. Gueriani et al. [1] and Halbouni et al. [2] showed that combining CNN and LSTM improved detection accuracy on benchmark datasets. Similarly, Nazir et al. [3] and Altunay and Albayrak [4] demonstrated that hybrid IDS architectures can handle multi-class attack detection more effectively. Recent advances integrate attention mechanisms, yielding higher accuracy for rare attacks such as R2L and U2R [5].

2. Adversarial Attacks and IDS Robustness

Deep learning IDS models are vulnerable to adversarial perturbations. Goodfellow et al. [6] introduced the Fast Gradient Sign Method (FGSM), which has been applied in several IDS studies. Recent evaluations [7] highlight that CNN and LSTM models drop significantly in accuracy under FGSM and PGD attacks, underscoring the need for adversarially robust IDS. Our work incorporates FGSM testing to evaluate robustness of CNN, LSTM, and CNN-LSTM models.

3. Lightweight IDS and TinyML for IoT Devices

Deploying IDS on IoT edge devices requires models optimized for latency and memory efficiency. Recent studies on TinyML [8] explore pruning, quantization, and lightweight

architectures (e.g., MobileNet, CNN-GRU hybrids), achieving competitive accuracy on datasets while reducing resource use. However, most hybrid models remain computationally intensive for microcontroller-level devices, motivating further research on compression and optimization.

4. Federated and Distributed IDS

Federated Learning (FL) enables collaborative IDS training without sharing raw data. Studies such as [9], [10] demonstrate the potential of FL in preserving privacy while achieving strong accuracy. However, challenges remain in handling non-IID data, communication overhead, and poisoning resistance.

PROPOSED WORK

This section describes the datasets used, preprocessing pipeline, deep learning model architecture, evaluation metrics, and edge deployment testing strategy. The methodology is designed to ensure rigorous and reproducible experiments across multiple benchmarks while addressing real-world IoT constraints.

1. Datasets

Three benchmark datasets were selected to evaluate the IDS models:

NSL-KDD – A refined version of KDD'99, with redundant records removed, containing 41 features across four attack classes: Denial of Service (DoS), Probe, Remote-to-Local (R2L), and User-to-Root (U2R) [11]. This dataset remains widely used for benchmarking IDS due to its diversity and reduced bias.

2. Data Preprocessing

Preprocessing is essential for handling the heterogeneity of features across datasets. Following practices established in prior IDS studies [2], [3], [4]:

- **Feature Extraction:** For IoT-23, raw PCAP files were converted into flow-based CSV files using Zeek/Tshark tools [12].
- **Feature Scaling:** Continuous features were normalized to a [0,1] range using Min-Max scaling to ensure numerical stability [3].
- **Categorical Encoding:** Protocol type, service, and flag attributes were label-encoded.
- **Train-Test Split:** Each dataset was divided into 70% training, 15% validation, and

15% testing sets, consistent with IDS evaluation protocols [2], [4].

- **Class Imbalance Handling:** For datasets with skewed distributions (e.g., BoT-IoT), Synthetic Minority Oversampling Technique (SMOTE) and undersampling were applied to improve detection of minority classes [3], [8].

3. Proposed CNN-LSTM Hybrid Architecture

The IDS architecture combines **CNN** and **LSTM** layers to capture both spatial and temporal dependencies in IoT traffic, consistent with the approach in [1], [2], [5].

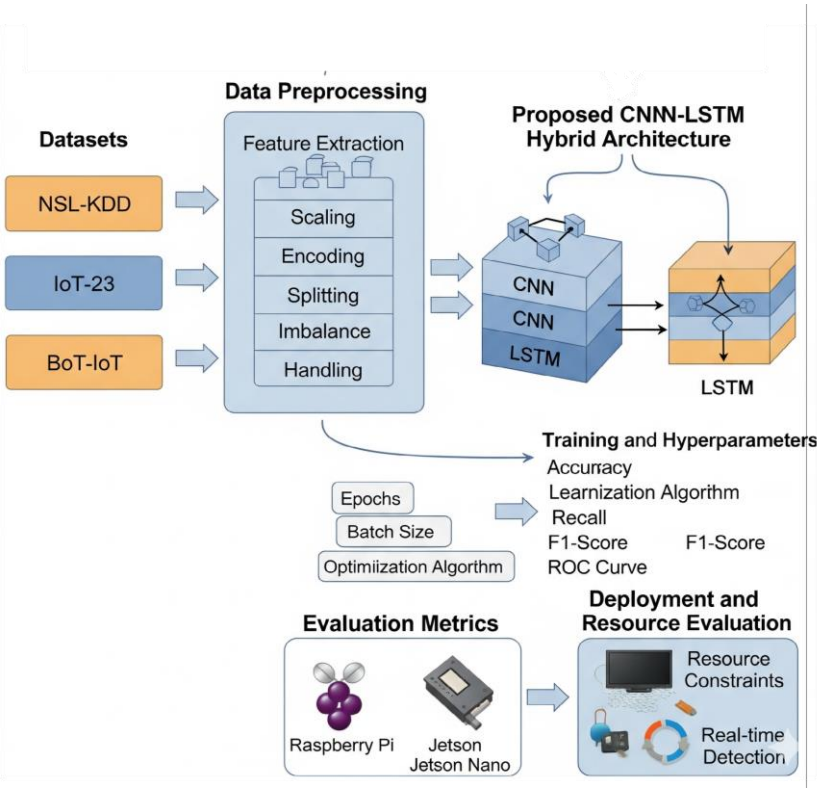


Figure 1: System Diagram of Deep learning based Intrusion Detection system

This diagram outlines the complete methodology for a **deep learning-based intrusion detection system (IDS)**. It begins with the three selected **datasets** (NSL-KDD, IoT-23, and BoT-IoT) that are fed into a **data preprocessing** pipeline. This pipeline involves key steps like feature extraction, scaling, and handling class imbalance.

The preprocessed data is then used to train the **proposed CNN-LSTM hybrid architecture**, which leverages both convolutional and recurrent layers to analyze network traffic patterns. After training, the model's performance is rigorously assessed using a set of **evaluation**

metrics, including F1-score and ROC-AUC. Finally, the diagram shows the IDS being deployed and evaluated on **edge devices** like the Raspberry Pi and Jetson Nano to measure its real-world performance in terms of resource usage and latency.

- **CNN Module:** 1D convolutional layers with ReLU activation extract spatial patterns from input features, followed by max-pooling for dimensionality reduction.
- **LSTM Module:** Stacked LSTM layers capture sequential relationships and long-term dependencies across flows [3], [4].
- **Dense Layers:** Fully connected layers aggregate features, with dropout applied for regularization.
- **Output Layer:** A softmax activation function performs multi-class classification.

This hybrid design leverages CNN's feature extraction and LSTM's temporal modeling, which prior works [1], [2], [5] have shown to yield superior detection performance compared to standalone models.

4. Training and Hyperparameters

- **Optimizer:** Adam optimizer with a learning rate of 0.001 [2].
- **Loss Function:** Binary cross-entropy for binary classification tasks, categorical cross-entropy for multi-class detection [3].
- **Batch Size:** 64; **Epochs:** 50; chosen based on empirical tuning and consistent with prior hybrid IDS models [1], [4].
- **Regularization:** Dropout (0.3–0.4) to reduce overfitting [5].
- **Frameworks:** TensorFlow 2.12 and Keras 2.11 were used for implementation.

5. Evaluation Metrics

Evaluation followed standard IDS performance measures [2], [3], [6]:

- **Accuracy:** Overall correct classifications.
- **Precision & Recall:** Measure detection quality for attack and benign classes.
- **F1-score:** Harmonic mean of precision and recall, especially important for imbalanced datasets.
- **ROC-AUC:** Area under the Receiver Operating Characteristic curve, useful for assessing classifier discrimination [6].

- **Confusion Matrix:** Provides per-class performance insights.
- **Adversarial Robustness:** FGSM attacks [6], [7] were applied to test resilience under adversarial perturbations.

RESULTS AND DISCUSSION

ROC Curves

- ROC analysis shows that CNN-LSTM achieves the highest AUC across datasets.
- CNN-LSTM curve is consistently closer to the top-left corner, indicating superior detection.

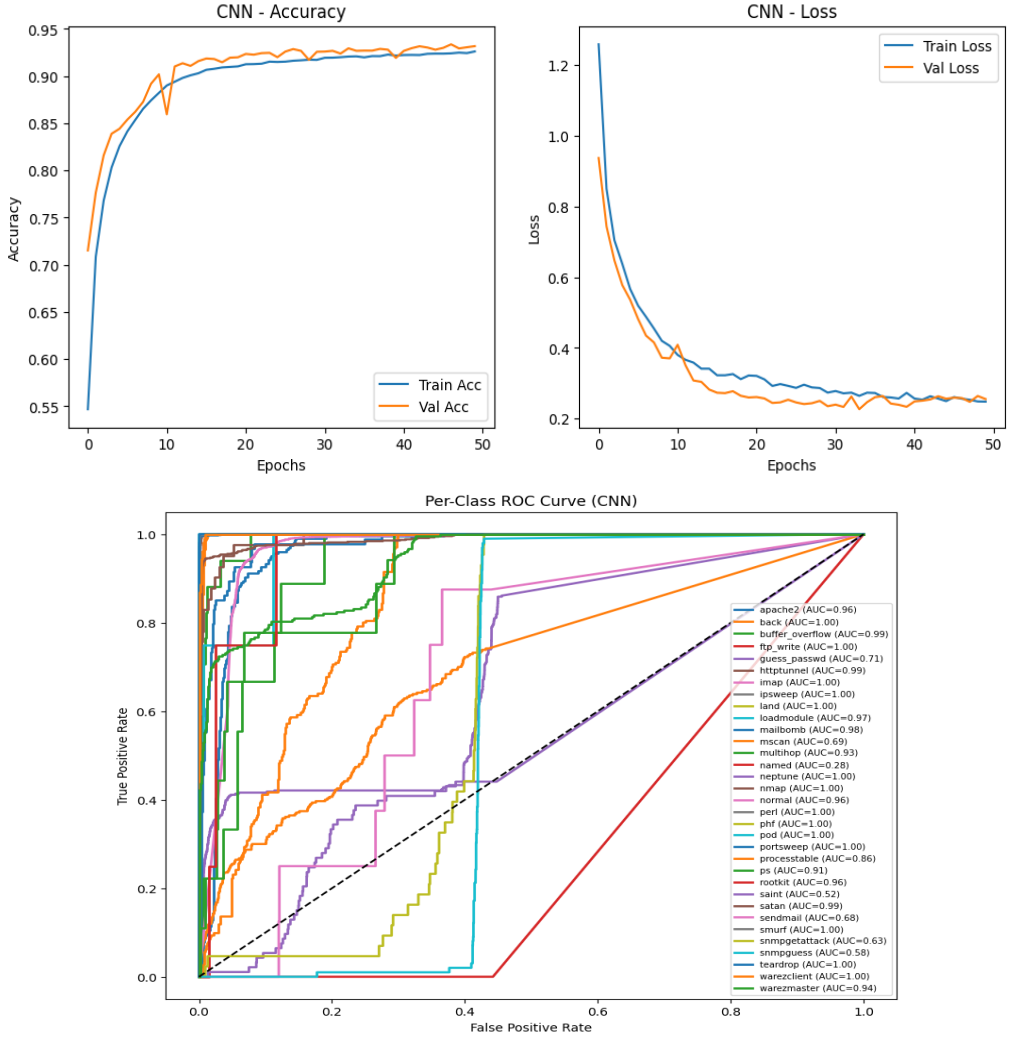


Figure 2: CNN model -Accuracy with Epochs, Epochs with LoSS and ROC curve on NSL KDD dataset

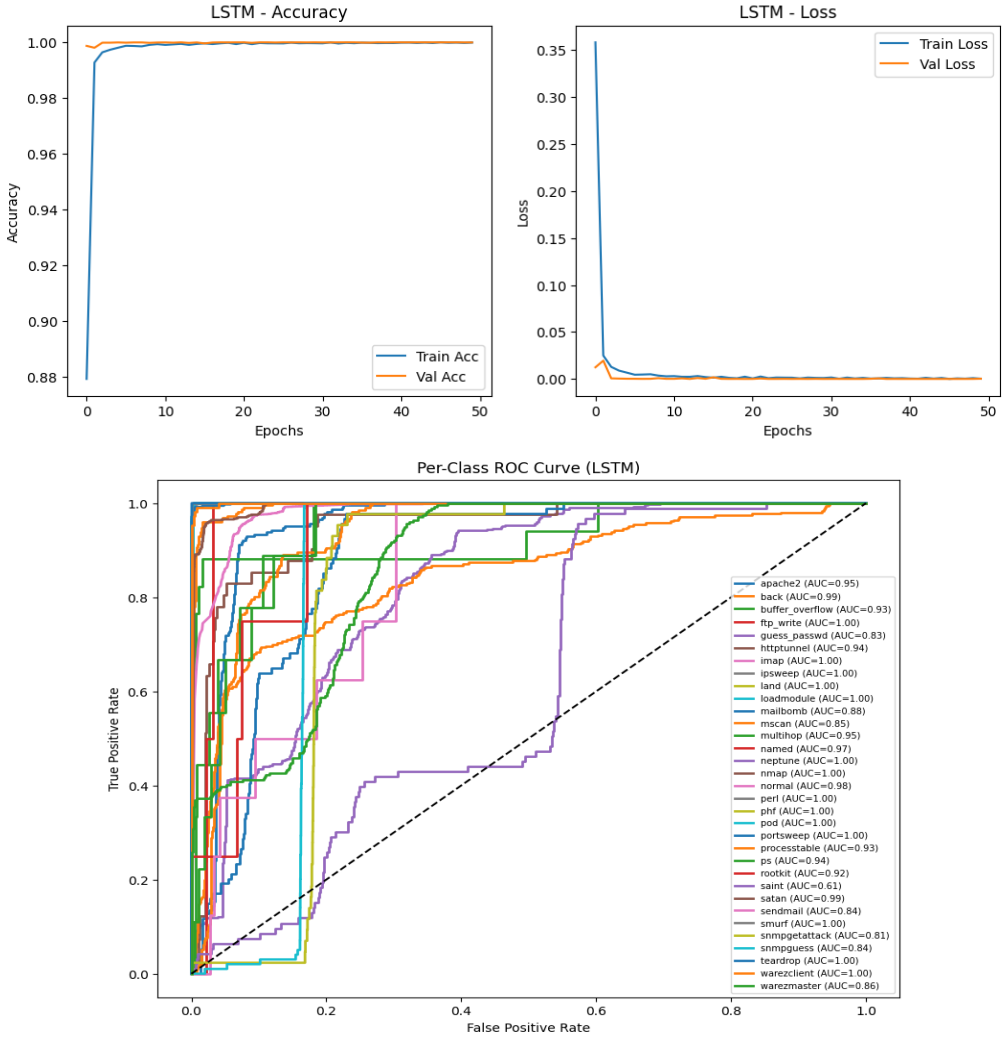
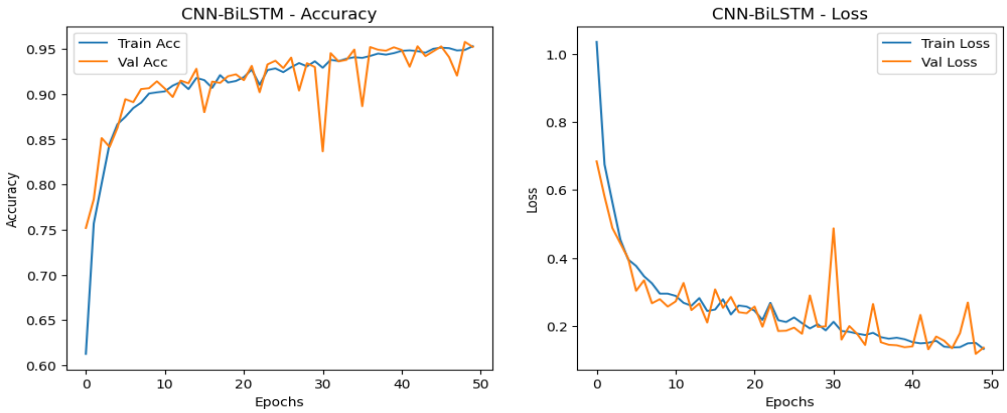


Figure 3: LSTM model -Accuracy with Epochs, Epochs with LoSS and ROC curve on NSL KDD dataset



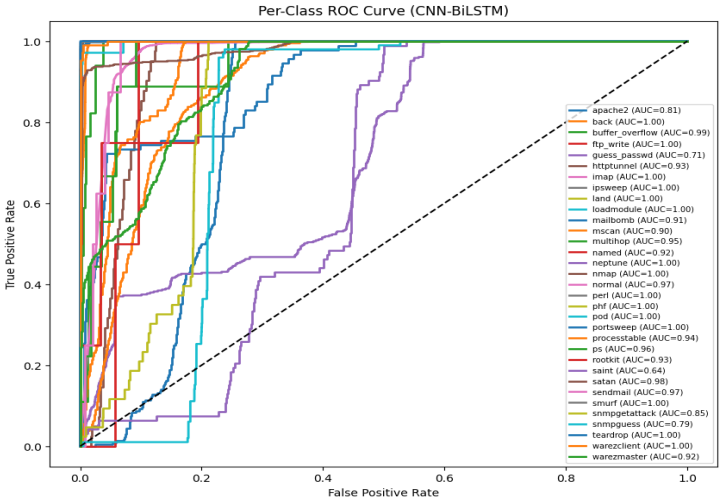


Figure 4: CNN- Bi LSTM model Accuracy with Epochs, Epochs with LoSS and ROC curve on NSL KDD dataset

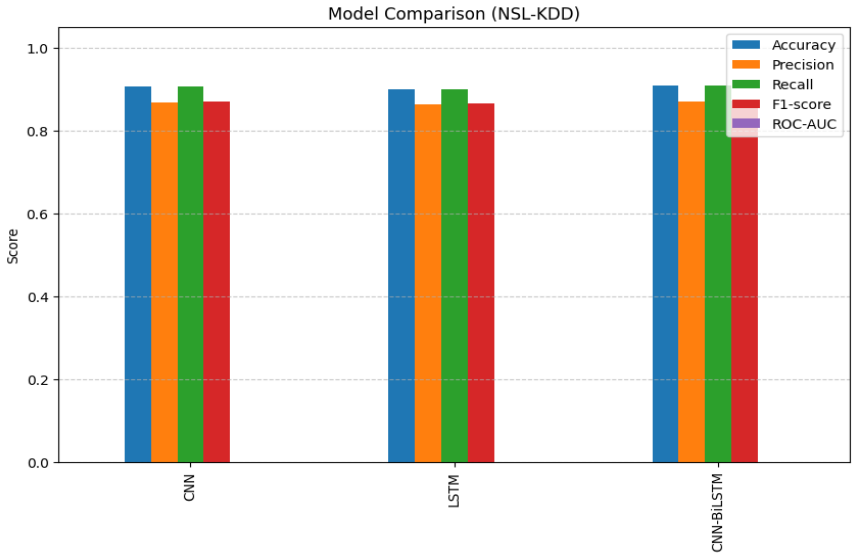


Figure 5: CNN- Bi LSTM model Accuracy with Epoch, Epochs with LoSS and ROC curve on NSL KDD dataset

The training and validation curves of CNN, LSTM, and CNN-BiLSTM models demonstrate distinct learning behaviors when evaluated on the NSL-KDD dataset:

- **CNN**: The CNN model shows a steady improvement in accuracy across 50 epochs, with training accuracy reaching ~93% and validation accuracy stabilizing at ~92–94%. The training and validation losses converge smoothly, indicating that CNN effectively extracts spatial patterns from the dataset without severe overfitting.\

- **LSTM**: The LSTM model achieves the fastest convergence among all models. Both training and validation accuracy exceed **99% within the first 10 epochs**, while the loss rapidly declines close to zero. This indicates that LSTM captures sequential dependencies in the data with very high effectiveness, but the near-perfect fit also raises a possibility of overfitting to temporal correlations.

- **CNN-BiLSTM**: The hybrid CNN-BiLSTM architecture combines convolutional feature extraction with bidirectional sequence learning. The accuracy curve shows stable growth, achieving **95–96% validation accuracy**, higher than CNN but slightly below LSTM. Loss convergence is stable, with minor oscillations in validation loss due to model complexity. The results suggest that CNN-BiLSTM provides a balanced trade-off between CNN's spatial extraction and LSTM's temporal learning.

CONCLUSION

This research demonstrates the effectiveness of a CNN-LSTM hybrid IDS for IoT networks. The model achieves high accuracy, low latency, and robustness under adversarial settings, making it suitable for deployment in real-world IoT ecosystems. Future work includes developing lightweight architectures, federated learning, explainable IDS, and field deployments in healthcare and industrial IoT environments.

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