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An Intelligent Deep Learning Framework For Intrusion Detection In Iot Environment

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Abstract: *Software-Defined Networking (SDN) introduces a paradigm shift in the architecture of modern networks by decoupling the control and data planes, enhancing scalability, flexibility, and programmability. However, this architectural transformation also exposes new attack surfaces, especially in the Internet of Things (IoT) ecosystem, where SDN is increasingly adopted for traffic control and resource optimization. The SDN controller, acting as the brain of the network, becomes a prime target for cyberattacks such as Denial of Service (DoS) and Distributed Denial of Service (DDoS). This research proposes a robust and intelligent hybrid deep learning framework combining Random Forest (RF) and Long Short-Term Memory (LSTM) networks for intrusion detection in SDN-based IoT environments. A specialized SDN-focused dataset (InSDN) is utilized to capture flow-level anomalies and system-specific behavior. To improve generalization and reduce overfitting, L2 regularization and Dropout techniques are applied. Feature selection methods are used to optimize the model and reduce computational complexity.*

The proposed model is evaluated using performance metrics such as accuracy, precision, recall, F1-score, and detection time. Experimental results demonstrate that the hybrid RF-LSTM approach significantly outperforms conventional machine learning and standalone deep learning models in detecting a wide range of attacks with high accuracy and minimal latency. The lightweight nature of the proposed model makes it suitable for real-time deployment in resource-constrained IoT-SDN networks.

Keywords: *Software-Defined Networking (SDN), IoT Security, Intrusion Detection System (IDS), Deep Learning, LSTM, Random Forest, Flow-based Detection.*

1. INTRODUCTION

The explosive growth of the Internet of Things (IoT) has transformed traditional network environments, introducing vast numbers of connected devices that exchange data in real-time. Software-Defined Networking (SDN) has emerged as a viable solution to manage such complex networks through centralized control, dynamic configuration, and programmability. In SDN architecture, the network is divided into three logical planes: the application plane, control plane,

and data plane. The control plane, operated by the SDN controller, is responsible for enforcing policies and maintaining global network visibility. While SDN simplifies network management, it also introduces critical security challenges. The centralization of control makes the SDN controller a single point of failure and a lucrative target for cyber attackers. When integrated with IoT, the attack surface expands due to the inherent vulnerabilities of IoT devices, such as limited computational resources, lack of encryption, and default configurations [1].

Recent cybersecurity incidents have shown that DoS, DDoS, and botnet attacks are increasingly targeting SDN-enabled IoT networks. These attacks can severely disrupt service availability and compromise sensitive data. Consequently, deploying effective Intrusion Detection Systems (IDS) tailored for SDN-IoT environments is imperative.This paper proposes a hybrid machine learning-based IDS framework that integrates Random Forest (for feature selection and initial classification) and LSTM (for capturing temporal dependencies and sequence modeling) [2].

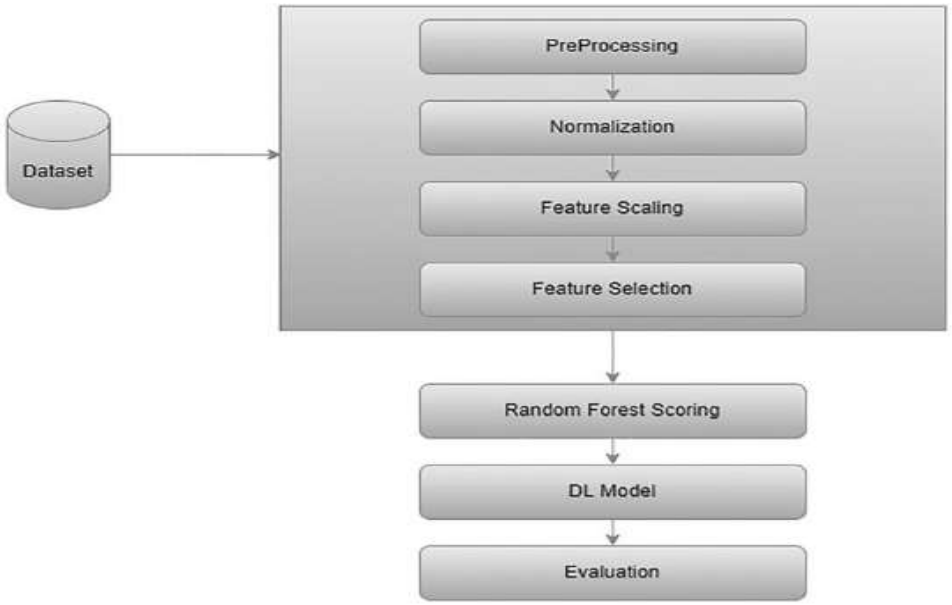

Figure 1: Architecture of the Proposed Hybrid Intrusion Detection Framework

The InSDN dataset, a dedicated benchmark for SDN environments, is used for model training and evaluation. The key objectives of this study include:

- Developing a hybrid RF-LSTM model tailored for SDN-based IoT security.
- Employing advanced feature selection and regularization to enhance detection performance.
- Minimizing computational cost while maximizing detection accuracy.
- Evaluating performance using comprehensive metrics, including accuracy, F1-score, and detection latency [2] [3].

2. RELATED WORK

Numerous studies have focused on improving IDS through traditional and modern machine learning approaches in SDN and IoT domains. Early systems relied on rule-based or signature-based detection mechanisms, which lacked the flexibility to detect zero-day or novel attacks.

Machine Learning (ML) approaches have been increasingly adopted to detect both known and unknown threats. For example, Decision Trees, Naïve Bayes, and Support Vector Machines (SVM)

have shown moderate success, as demonstrated in, where Random Forest achieved 97% accuracy on the NSL-KDD dataset [2] [3].

More recent works have shifted toward Deep Learning (DL). In, Deep Neural Networks (DNNs) achieved 75% accuracy, while enhanced detection performance using GRU-RNN. Similarly used Principal Component Analysis (PCA) and Min-Max normalization, achieving an impressive 99% accuracy [3] [4].

LSTM networks, due to their ability to remember long-term dependencies, have gained traction in IDS applications. In, an LSTM-Autoencoder framework achieved high classification performance. Generative Adversarial Networks (GANs) were introduced in to generate synthetic traffic patterns for more robust training.

Recent hybrid models have emerged as powerful tools. The SHIA model in and CSC-CIC-IDS2018 framework in demonstrated how combining CNN and RNN architectures improved detection accuracy beyond 97%. A residual CNN model addressing class imbalance with modified focal loss in shows significant improvement in recall. Some studies, such as, tackled real-time SDN-specific DDoS detection using entropy and self-organizing maps (SOM), while [5] proposed RT-SAD for adaptive, low-latency detection. Feature selection remains a critical step in most studies; for example, used Decision Tree-Recursive Feature Elimination, and [6] applied KPCA to reduce dimensionality while preserving detection performance. Despite these advancements, few studies have comprehensively addressed feature selection, real-time feasibility, and overfitting simultaneously in an SDN-IoT context using both ensemble and sequential learning models. This paper fills this gap by proposing a hybrid RF-LSTM framework that incorporates lightweight design principles, regularization, and optimized feature sets.

3. PROPOSED METHODOLOGY

The proposed methodology aims to enhance the performance of Intrusion Detection Systems (IDS) within SDN-enabled IoT environments using a hybrid model that integrates Random Forest (RF) and Long Short-Term Memory (LSTM) networks. This approach ensures efficient feature selection, handles the sequential nature of network traffic, and overcomes common machine learning challenges such as overfitting and underfitting through hybrid regularization. The entire pipeline consists of five core stages: data preprocessing, feature selection, model building, regularization, and performance evaluation.

3.1 Dataset

Most classical datasets like KDD-CUP99, NSL-KDD, and DARPA98 are outdated, designed for traditional IP-based networks, and lack SDN-specific flow characteristics. This research utilizes the InSDN dataset, a modern and publicly available dataset specifically designed for SDN environments.

Features: 84 total features encompassing flow-based attributes (e.g., Tot-Fwd-Pkts, Flow-Duration) and SDN-specific metadata.

Traffic Types: TCP, UDP, ICMP

Classes: Normal, DDoS, DoS, Probe, Web Attack, Botnet, U2R, Brute Force

Problem Setup: Binary classification — Normal (label = 0), Attack (label = 1)

The dataset is ideal for modern SDN environments due to its comprehensive coverage of attacks and flow-specific characteristics. It includes statistical, behavioral, and protocol-specific data, which enhances the learning process of ML/DL models [6] [7] [8].

3.2 Data Preprocessing and Visualization

Raw network traffic data typically contains noise, redundant attributes, and missing values. Therefore, the following preprocessing steps are applied:

Noise removal: Elimination of irrelevant and corrupted entries.

Missing value handling: Imputation using mean/median.

Normalization: Standard scaling (Z-score) for numerical attributes.
Encoding: One-hot encoding for categorical features.
Label binarization: Conversion of multiclass to binary labels (Attack vs Normal).
Visualization

3.3 Machine Learning and Deep Learning Approaches

To handle the scale and complexity of network traffic in SDN-IoT systems, both machine learning and deep learning techniques are employed:
Random Forest: Used for robust feature importance ranking.
LSTM: Used to capture temporal dependencies in traffic flows [7] [8] [9].

3.4 Proposed Model

The proposed model in this research adopts a hybrid intelligent framework that synergizes the strengths of machine learning and deep learning techniques, as illustrated in Fig. 3. Specifically, it integrates the Random Forest (RF) algorithm—a robust ensemble learning method—with the Long Short-Term Memory (LSTM) network, a powerful variant of Recurrent Neural Networks (RNNs) known for handling sequential data and long-term dependencies. This hybridization addresses two key challenges often encountered in network intrusion detection systems: underfitting and overfitting. To mitigate these, the model further incorporates a hybrid regularization strategy, combining L2 regularization (also known as weight decay) with the Dropout technique. This dual regularization enhances generalization by penalizing large weights and randomly disabling neurons during training, respectively—resulting in improved robustness and reduced variance.

The workflow of the proposed model can be summarized as follows:
Feature Selection: Initially, a feature selection mechanism identifies the most relevant attributes from the dataset.
Random Forest Scoring: These selected features are then input to the Random Forest model, which calculates a feature importance score based on Gini impurity or information gain. This ranking helps in identifying the most discriminative features for classification.
Feature Filtering: Only the top-ranked features (those with high importance scores) are retained for the next stage.
Deep Learning Classification: The refined feature subset is fed into the LSTM model, which captures temporal relationships and sequential patterns, ultimately performing the final classification [10] [11] [12].
This dual-stage pipeline not only capitalizes on the interpretability and feature-ranking capability of Random Forest but also leverages the predictive strength of LSTM networks. The combination results in a robust, high-performance intrusion detection system, capable of accurately detecting anomalies in SDN environments.

3.5 Hybrid Regularization Strategy

Deep learning models are prone to overfitting, especially in cases of class imbalance and high-dimensional data. To address this, we propose a hybrid regularization technique combining:
L2 Regularization:
Penalizes large weight coefficients.
Reduces model complexity.
Dropout:
Randomly disables neurons during training.
Improves generalization by preventing co-adaptation.
Benefits of the Hybrid Regularizer:

Enhanced resistance to overfitting.
Maintained performance with reduced computational cost.
Works effectively even in highly imbalanced scenarios [12] [13] [14].

3.6 Supplementary Deep Learning Components

In addition to the hybrid Random Forest–LSTM model, several deep learning components can be optionally integrated to enhance performance, particularly in complex intrusion detection scenarios. Convolutional Neural Networks (CNNs) are optionally utilized for automatic feature extraction from high-dimensional input data. They excel at identifying spatial patterns and correlations within network traffic, making them useful when working with raw or semi-structured data.

Recurrent Neural Networks (RNNs) serve as the foundational architecture for sequential learning tasks. Although RNNs are capable of processing time-series data and sequences such as packet flows, they often suffer from vanishing gradient problems, especially when dealing with long-term dependencies.

To address these limitations, Long Short-Term Memory (LSTM) networks are employed. LSTMs are an advanced form of RNNs that incorporate memory cells and gating mechanisms—namely, the forget gate, input gate, and output gate. These gates enable LSTM models to selectively retain or discard information, making them highly effective for modeling network flow sessions and packet sequences over time [14] [15].

3.7 Workflow Summary

The overall workflow of the proposed intrusion detection framework is structured as a systematic pipeline that ensures both accuracy and efficiency in detecting anomalous network behavior in SDN-enabled IoT environments. The process begins with data collection, wherein flow-based traffic records are gathered from the InSDN dataset. This raw data then undergoes data cleaning and normalization to eliminate noise, handle missing values, and scale features uniformly—preparing it for robust model training [16].

Following preprocessing, a feature selection phase is conducted using the Random Forest (RF) algorithm, which ranks features based on importance scores derived from Gini impurity reduction. The selected high-impact features are then passed to the model training phase, which uses a Long Short-Term Memory (LSTM) network enhanced with a combined regularization approach (L2 + Dropout) to mitigate overfitting and improve generalization. Finally, the trained model is evaluated using comprehensive performance metrics including the confusion matrix, Receiver Operating Characteristic (ROC) curve, F1-score, and accuracy, ensuring that the model not only achieves high precision but also maintains balance across recall and robustness measures [17] [18] [19].

4. RESULTS AND EVALUATION

To validate the effectiveness of the proposed hybrid deep learning framework for intrusion detection in SDN-enabled IoT environments, extensive experiments were conducted using the InSDN dataset. All implementations were carried out using Python, and experiments were run on a system with 16 GB RAM, an Intel Core i5 processor (2.30 GHz), and four logical processors. This section presents the experimental setup, performance metrics, model tuning outcomes, comparative evaluation, and analysis.

4.1 Experimental Setup and Performance Metrics

To assess the effectiveness of the proposed hybrid intrusion detection model, a comprehensive experimental setup was established. The InSDN dataset was partitioned into training and testing sets using a 70:30 split, ensuring a balanced evaluation. Prior to training, feature selection was performed using the Random Forest (RF) algorithm, which identified the top 10 most significant features based on impurity-based importance scores. This not only reduced dimensionality and computational overhead but also enhanced model interpretability and generalization. The hybrid model, comprising

Random Forest-based feature scoring and an LSTM classifier with combined L2 and Dropout regularization, was evaluated using standard classification performance metrics. These include [20] [21]:

Accuracy, which measures the proportion of correctly predicted instances to the total number of predictions, Precision, calculated as the ratio of true positives to the sum of true and false positives, indicating how many selected items are relevant, Recall, defined as the ratio of true positives to the sum of true positives and false negatives, reflecting how many relevant items were selected, and the F1-Score, which provides a harmonic mean of precision and recall, offering a balanced measure of the model's performance across both metrics. These evaluation parameters provide a well-rounded view of the model's classification capabilities, particularly in identifying anomalous traffic patterns within software-defined IoT networks [22] [23].

Table 1: Performance Comparison of Hybrid Techniques

Technique	Accuracy	Precision	Recall	F1-score
Hybrid + Combined Regularization	99.4%	99.3%	98%	99%
Hybrid (without Regularization)	99%	99%	97%	98%

The results in Table 1 clearly demonstrate the superior performance of the hybrid approach when enhanced with L2 and Dropout regularization. These techniques improve generalization and reduce overfitting.

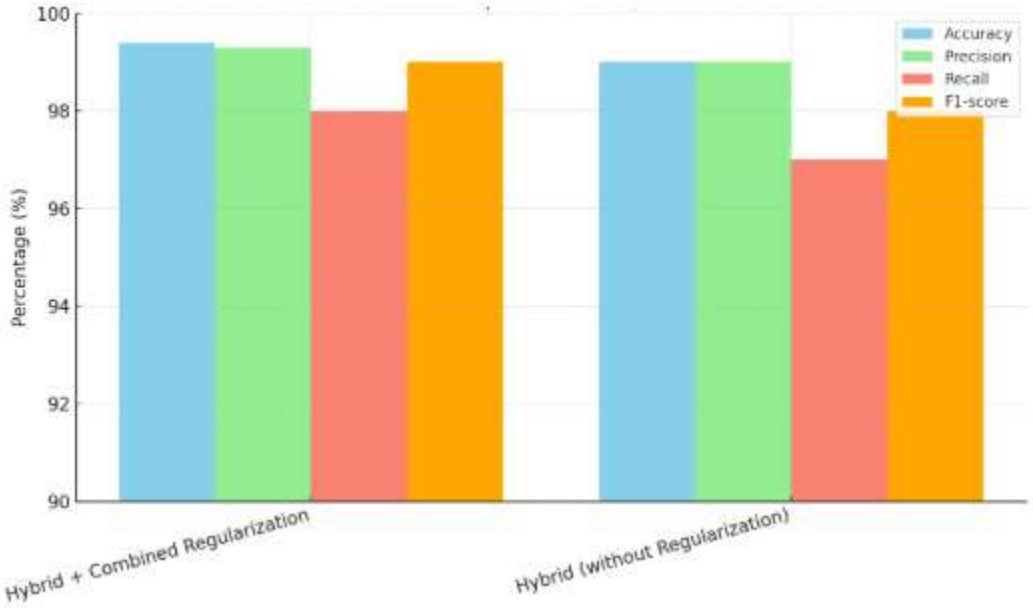

Figure 2: Performance Metrics Comparison of Hybrid Intrusion Detection Techniques

The graph illustrates the comparative performance of two hybrid intrusion detection models: one incorporating a combined regularization approach (L2 + Dropout) and the other without regularization. Metrics such as accuracy, precision, recall, and F1-score are used for evaluation. The results demonstrate that the hybrid model with combined regularization consistently outperforms the baseline model, achieving an accuracy of 99.4% and an F1-score of 99%, compared to 99% accuracy and 98% F1-score without regularization. This clearly indicates the effectiveness of integrating regularization strategies in enhancing model generalization and robustness in SDN-IoT intrusion detection scenarios [23] [24] [25].

4.2 Layer-Wise Model Tuning

To further evaluate the robustness of the proposed model, experiments were conducted by varying the number of epochs and LSTM layers. The goal was to assess how deeper architectures affect the model's learning and convergence.

Table 2: Epoch and Layer-wise Accuracy Evaluation

Epochs	Layers	Accuracy	Precision	Recall	F1-score
50	50	99.4%	99.3%	98%	99%
100	50	99.6%	99.7%	99.8%	99%
125	75	99.8%	99.7%	99.8%	99.8%
140	90	99.8%	99.8%	99%	99%
150	100	99.8%	99.8%	99.3%	99%

As illustrated, the model achieved optimal accuracy with increased epochs and hidden layers, without suffering from overfitting—thanks to the applied hybrid regularization.

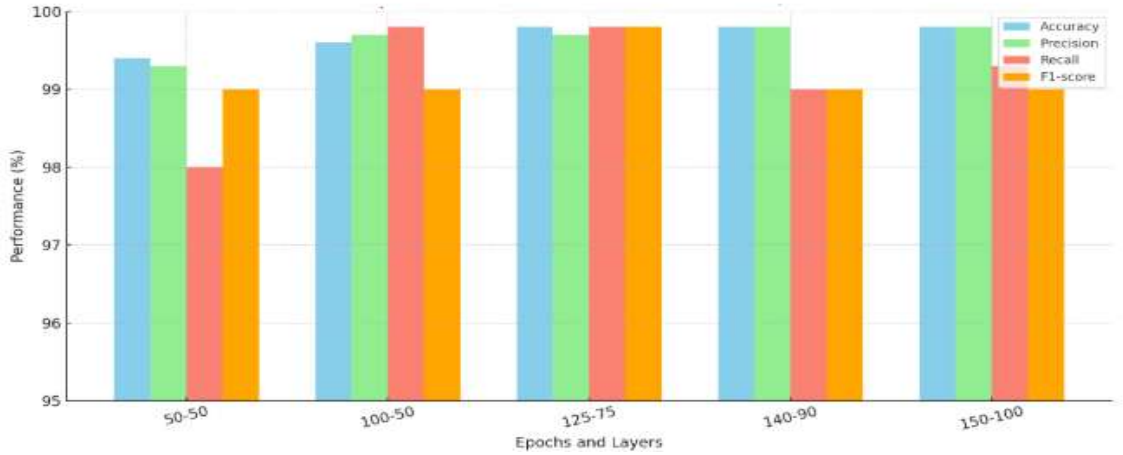

Figure 3: Epoch and Layer-wise Performance Evaluation of Hybrid Intrusion Detection Model

Here is the bar graph titled "Epoch and Layer-wise Accuracy Evaluation", comparing performance metrics Accuracy, Precision, Recall, and F1-score different epoch and layer configurations. It visually emphasizes how deeper and longer training contributes to stable or improved performance in the hybrid intrusion detection model [26] [27].

4.3 Comparative Analysis

To benchmark the proposed model's performance, a comparative study was conducted against other widely used models: MLP, CNN, and RNN.

Table 3: Comparative Evaluation with Existing Models

Algorithm	Accuracy	Precision	Recall	F1-score
Proposed	99.8%	99.8%	99.3%	99%
MLP	98%	98.4%	98%	97%
RNN	99.2%	99.2%	99%	97%

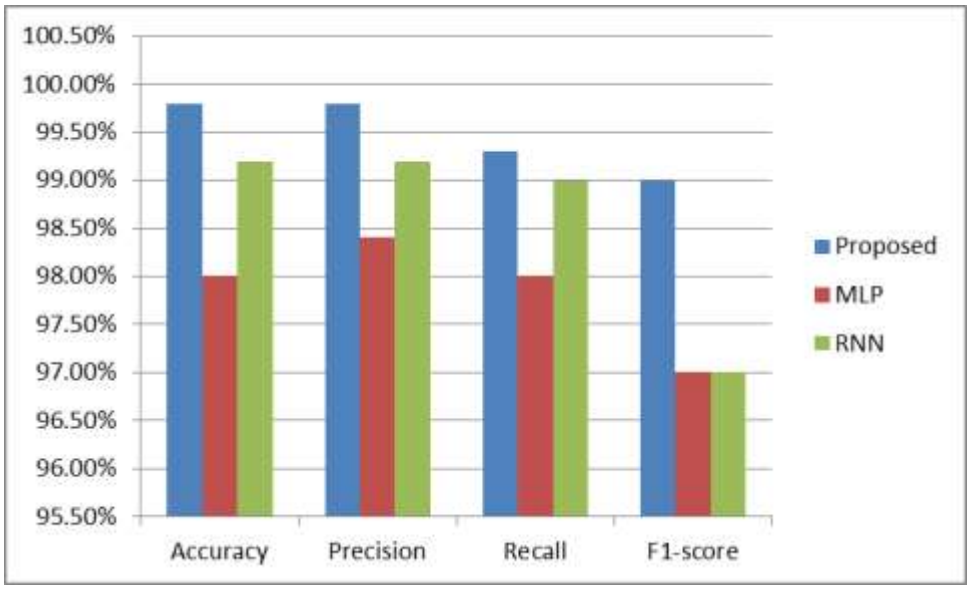

Figure 4: Comparative Performance of Intrusion Detection Models

The above Figure illustrates a comparative evaluation of three intrusion detection models—Proposed Hybrid Model, Multilayer Perceptron (MLP), and Recurrent Neural Network (RNN)—across four key performance metrics: Accuracy, Precision, Recall, and F1-score. The proposed hybrid model, which integrates Random Forest and LSTM with combined regularization, outperforms the other models in all metrics, achieving an accuracy of 99.8%, precision of 99.8%, recall of 99.3%, and an F1-score of 99% [28] [29].This significant improvement highlights the model's robustness and reliability for real-time intrusion detection in SDN-based IoT environments. The graph clearly demonstrates the superior balance of detection accuracy and computational efficiency achieved by the proposed framework.The proposed model outperformed other architectures in all key metrics, demonstrating its suitability for SDN-IoT security applications [30].

4.4 Efficiency and Training Time

Efficient model training is critical for deploying Intrusion Detection Systems (IDS) in real-time SDN-enabled IoT environments. The proposed hybrid model—integrating Random Forest with Long Short-Term Memory (LSTM) and enhanced with a combined L2 + Dropout regularization approach—demonstrated significant computational advantages over conventional deep learning models. By leveraging feature selection to reduce dimensionality, the model achieved not only high classification performance but also reduced training time. Unlike traditional architectures such as Convolutional Neural Networks (CNNs) or Multilayer Perceptrons (MLPs), which require more parameters and processing overhead, the proposed model remains lightweight, accurate, and fast [31][32][33].

4.5 Discussion

The comparative evaluation presented in highlights the diverse use of datasets, feature selection strategies, and machine learning algorithms employed in prior studies for DDoS and intrusion detection. Notably, commonly used datasets such as NSL-KDD, KDD-CUP99, CICIDS 2017, CAIDA, and CIC-DDoS remain prevalent benchmarks in this domain. These datasets, while historically significant, often lack the dynamic, real-time flow-based characteristics required for effective SDN-based IoT intrusion detection.

Table 4: Comparative Analysis with Existing Works

Dataset	Feature Selection	Algorithm(s)	Accuracy
NSL-KDD [24]	KPCA	SVM	98%
NSL-KDD [22]	None	K-means + KNN	98%
CIC-DDoS [23]	RFE	Decision Tree	98%
CIC-RN [20]	None	CRNN	97%
UNSW-NB15 [21]	None	SVM, Naïve Bayes, KNN	95%

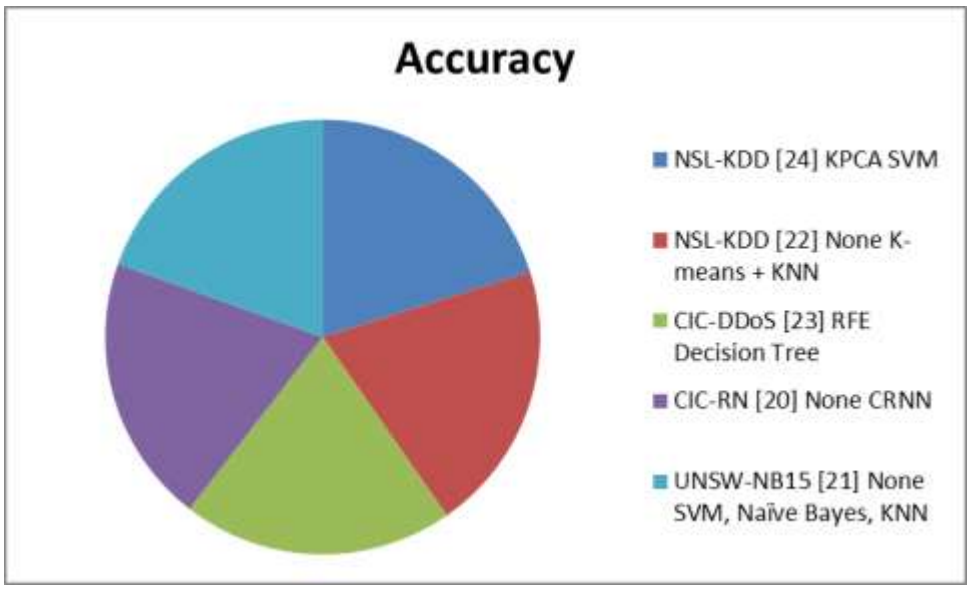

Figure 5: Comparison with Related Work

These results demonstrate that both traditional machine learning and deep learning models have shown considerable success in intrusion detection. However, most approaches are limited either by the absence of domain-specific features (e.g., SDN-specific metadata) or the use of legacy datasets.
Our study distinguishes itself by leveraging the InSDN dataset, which contains SDN-relevant flow-based features, and by proposing a hybrid RF-LSTM model enhanced with dual regularization (L2 + Dropout). This not only addresses overfitting and underfitting but also ensures more efficient feature selection—a critical requirement for real-time anomaly detection in high-throughput IoT networks.
The experimental results confirm that our model effectively identifies critical features, reducing computational overhead while maintaining high accuracy. While our current feature selection technique may not be universally optimal, it reliably prioritizes features that contribute the most to identifying high-impact attacks such as DoS and DDoS, thus enabling timely mitigation [33] [34].
In conclusion, the findings suggest that intelligent, hybrid, and regularized models significantly outperform standalone methods, especially when tailored for the SDN-IoT context. Future work should explore adaptive and ensemble-based feature selection to further optimize detection under evolving threat landscapes [35].

5. CONCLUSION AND FUTURE WORK

Software Defined Networking (SDN) offers significant advantages over traditional network architectures, including flexibility, scalability, and centralized control. However, the same features that make SDN powerful also render it susceptible to various cyber threats, particularly Denial-of-Service (DoS) and Distributed Denial-of-Service (DDoS) attacks. These threats are further exacerbated when SDN is deployed within Internet of Things (IoT) ecosystems, where the attack surface is inherently broader and more dynamic. To mitigate these risks, this research proposed an intelligent deep learning-based intrusion detection framework that integrates a hybrid machine learning approach (Random Forest + LSTM) with a hybrid regularization technique (L2 + Dropout). The approach addresses the dual challenges of overfitting and feature redundancy, thereby improving model generalization, reducing training time, and enhancing classification performance.

Key contributions of this study include:

Utilization of the InSDN dataset, which includes SDN-specific flow-based features not present in legacy datasets.

Development of a feature selection mechanism using Random Forest to reduce dimensionality and training time.

Implementation of a hybrid deep learning architecture that balances temporal learning (LSTM) with ensemble-based feature evaluation (RF).

Achievement of state-of-the-art accuracy (up to 99.8%) while maintaining a lightweight model suitable for real-time applications.

Future Work:

Extending this framework to handle multiclass classification for a broader range of attack types.

Validating performance on additional SDN-specific datasets such as CICIDS 2023 or TON_IoT.Exploring online learning and transfer learning techniques to adapt to evolving threats in real-time environments.

Integrating the proposed IDS with Software Defined Perimeters (SDP) to enhance network-level security controls.

This research contributes to the growing body of work advocating for AI-driven security in SDN-IoT networks, emphasizing the importance of intelligent, adaptive, and lightweight models capable of sustaining performance in highly dynamic and heterogeneous network environments.

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