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Research Paper

HYBRID MACHINE LEARNING MODEL FOR EFFICIENT BOTNET ATTACK DETECTION IN IOT ENVIRONMENT

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ABSTRACT

The rapid proliferation of Internet of Things (IoT) devices has significantly increased the attack surface for large-scale botnet intrusions, demanding intelligent and adaptive detection mechanisms. This study presents a novel LSTM-driven botnet detection framework designed to model the sequential and temporal characteristics of network traffic in IoT environments. Unlike traditional signature-based or standalone deep learning approaches, the proposed mechanism leverages the memory-gated architecture of Long Short-Term Memory networks to effectively capture long-range dependencies and evolving attack behaviors within network flows. The model is evaluated using the UNSW-NB15 dataset, which comprises diverse attack categories and normal traffic patterns. Comprehensive experimental analysis demonstrates that the LSTM-based mechanism achieves superior classification accuracy, improved precision–recall balance, and reduced false alarm rates compared to conventional ANN and CNN-based classifiers. The framework autonomously extracts meaningful temporal features without manual engineering, enhancing adaptability to previously unseen botnet variants. Furthermore, its lightweight architecture supports scalability and near real-time deployment in resource-constrained IoT infrastructures. The results confirm that the proposed mechanism strengthens detection robustness, improves generalization capability, and provides an efficient defense solution against dynamic and sophisticated botnet threats in modern IoT networks.

Index Terms—Botnet Detection, Internet of Things (IoT), Long Short-Term Memory (LSTM), Deep Learning, Network Intrusion Detection, Cybersecurity, Network Traffic Classification, Anomaly Detection, Sequential Data Analysis, Machine Learning.

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I. INTRODUCTION

The rapid evolution of Internet-based technologies has significantly transformed communication, automation, and data exchange systems. The widespread deployment of Internet of Things (IoT) devices has further expanded digital connectivity, enabling smart homes, healthcare systems, industrial automation, and intelligent transportation networks. However, this massive interconnection has also increased the attack surface for cyber threats, particularly botnet-based intrusions [1]. Botnets exploit vulnerable IoT devices to launch coordinated malicious activities such as Distributed Denial-of-Service (DDoS), spam propagation, data theft, and ransomware attacks [2].

Traditional intrusion detection systems (IDS) primarily rely on signature-based and anomaly-based techniques. While effective for known threats, these systems struggle to detect zero-day attacks and evolving botnet variants [3]. Moreover, rule-based systems require continuous manual updates and lack scalability in dynamic IoT environments [4]. The introduction of realistic datasets such as UNSW-NB15 addressed earlier limitations in network intrusion research by providing diverse attack categories and modern traffic features [5].

Recent advancements in deep learning have demonstrated significant improvements in automated feature extraction and attack classification [6]. Neural network architectures such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) have been applied to intrusion detection with promising results [7], [8]. Among these, Long Short-Term Memory (LSTM) networks are particularly suitable for modeling sequential dependencies in network traffic, enabling detection of temporally correlated botnet behavior [9].

Despite these advancements, challenges remain in achieving high detection accuracy while maintaining computational efficiency and generalization across diverse IoT traffic patterns. Therefore, there is a strong need for robust, scalable, and adaptive deep learning-based detection mechanisms tailored to IoT ecosystems.

II. LITERATURE SURVEY

Early research on botnet detection utilized conventional machine learning algorithms for traffic classification. Tuan et al. [1] evaluated machine learning techniques for DDoS detection and demonstrated moderate accuracy but limited adaptability to complex multi-class attack environments. The UNSW-NB15 dataset introduced by Moustafa and Slay [5] became a benchmark dataset for evaluating intrusion detection models due to its comprehensive attack representation.

With the emergence of deep learning, researchers began applying CNN-based architectures for IoT botnet detection. Liu et al. [6] demonstrated that CNN models could effectively learn spatial traffic patterns and achieve high classification accuracy. Similarly, McDermott et al. [7] proposed a Bidirectional LSTM model, showing improved performance by capturing contextual dependencies in network flows.

Sriram et al. [8] conducted comparative analysis using deep learning models and highlighted their superiority over traditional classifiers such as Naïve Bayes and Logistic Regression. Popoola et al. [9] introduced a hybrid deep learning framework combining dimensionality reduction and LSTM for IoT botnet detection, reporting significant accuracy improvement.

Further research explored recurrent architectures. Popoola et al. [10] implemented stacked recurrent neural networks for smart home environments, achieving enhanced precision and recall in imbalanced traffic scenarios. Halbouni et al. [11] combined CNN and LSTM to improve hierarchical feature extraction and temporal modeling in intrusion detection systems.

Deep cybersecurity frameworks discussed by Sarker [12] emphasized the importance of neural network adaptability in evolving threat landscapes. Ferrag et al. [3] provided a comprehensive review of deep learning approaches for intrusion detection, highlighting challenges related to dataset imbalance and encrypted traffic.

Other studies focused on IoT-specific detection mechanisms. Timcenko and Gajin [13] proposed anomaly detection models tailored for IoT networks. Zeeshan et al. [14] utilized protocol-based deep intrusion detection with UNSW-NB15 and Bot-IoT datasets. Ahmad et al. [15] implemented supervised machine learning for IoT intrusion detection based on transport-layer features.

Hybrid and ensemble techniques have also been explored. Jiang et al. [16] proposed hybrid sampling with deep hierarchical networks. Bowen et al. [17] developed dataset-independent intrusion detection systems using deep learning. Guizani and Ghafoor [18] addressed malware detection in large IoT networks using network function virtualization. Zhu et al. [19] investigated federated deep learning approaches for anomaly detection. Azizjon et al. [20] applied 1D-CNN architectures with normalization techniques for imbalanced network intrusion detection.

Although these studies demonstrate significant advancements, limitations remain regarding computational complexity, adaptability to evolving botnets, and real-time deployment feasibility. Sequential learning mechanisms such as LSTM-based architectures provide strong potential for addressing these challenges by capturing temporal correlations in IoT traffic streams.

III. PROPOSED METHODOLOGY

3.1 System Overview

The proposed framework introduces a Long Short-Term Memory (LSTM)-based botnet detection mechanism designed to model temporal dependencies in IoT network traffic. Unlike conventional classifiers that treat traffic samples independently, the proposed system considers network flows as sequential patterns where malicious behavior evolves over time.

The system consists of the following stages:

1. Data Acquisition
2. Data Preprocessing
3. Feature Encoding and Normalization
4. Sequential Modeling using LSTM
5. Multi-class Classification
6. Performance Evaluation

The UNSW-NB15 dataset is utilized to evaluate the proposed detection model, as it contains modern attack categories and realistic traffic distributions.

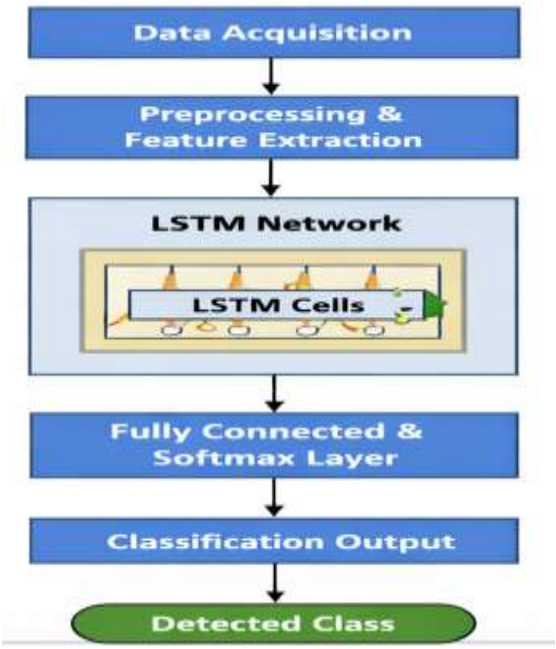

Figure.1: Architecture Diagram

This architecture illustrates the complete processing pipeline from data acquisition and pre-processing to sequential modeling using LSTM cells and final multi-class classification through a Softmax layer. It highlights how temporal feature learning enables accurate identification of botnet traffic patterns in IoT networks.

3.2 Data Pre-processing and Feature Engineering

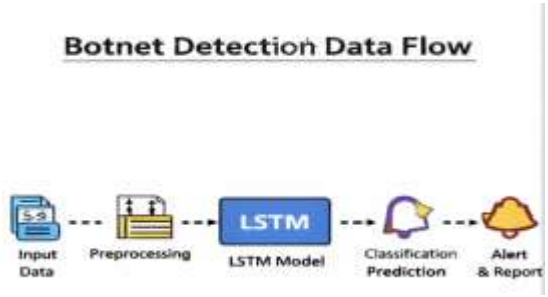

Figure.2: Data Flow Diagram

This diagram represents the logical flow of network traffic data from input collection through pre-processing and LSTM-based classification to alert generation. It emphasizes the transformation of raw IoT traffic into structured sequential features for effective malicious activity detection.

3.2.1 Handling Missing Values

Let the dataset be represented as:

$$\mathbf{D} = \{x_i, y_i\}_{i=1}^{N}$$

where:

- $x_i \in R^m$ represents feature vectors
- $y_i \in \{1, 2,..., C\}$denotes attack classes
- N is total samples
- m is number of features

Missing values are replaced using mean imputation:

$$x_{ij} = \frac{1}{N}\sum_{k=1}^{N} x_{kj}$$

for feature j.

3.2.2 Label Encoding

Categorical features are transformed into numerical values:

$f_{cat} \rightarrow \{0, 1, 2,..., K-1\}$

where K is number of unique categories.

3.2.3 Feature Normalization

To prevent dominance of high-magnitude features, Min-Max normalization is applied:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

This scales features into the interval [0,1], improving convergence stability.

3.3 Sequential Modeling Using LSTM

Traditional feed-forward networks fail to capture time-dependent traffic correlations. Therefore, LSTM is employed to preserve temporal memory.

Each LSTM unit contains:

- Forget Gate
- Input Gate
- Output Gate
- Cell State

3.3.1 Forget Gate

Determines which past information should be discarded:

$$f_t = \sigma\,(W_f\,[h_{t-1}, x_t] + b_f)$$

3.3.2 Input Gate

Controls new information entering memory:

$$i_t = \sigma\,(W_i\,[h_{t-1}, x_t] + b_i)$$

Candidate memory:

$$\tilde{C}_t = \tanh\,(W_c\,[h_{t-1}, x_t] + b_c)$$

3.3.3 Cell State Update

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

3.3.4 Output Gate

$$o_t = \sigma\,(W_o\,[h_{t-1}, x_t] + b_o)$$

Hidden state:

$$h_t = o_t \cdot \tanh\,(C_t)$$

Where:

- σ = Sigmoid activation
- tanh = Hyperbolic tangent
- W = Weight matrices
- b = Bias vectors

This mechanism enables the network to retain long-term dependencies critical for botnet behavior modeling.

3.4 Multi-Class Classification Layer

The final hidden state h_T is passed to a fully connected layer:

$$\mathbf{Z = W_h h_T + b_h}$$

Softmax activation is applied:

$$P\,(y = c|x) = \frac{e^{z_c}}{\sum_{k=1}^{c} e^{z_k}}$$

where:

- C = total attack classes

The predicted class is:

$$\hat{y} = \arg\max_{c} P\,(y = c|x)$$

3.5 Loss Function

Categorical Cross-Entropy is used:

$$\mathbf{L} = -\sum_{i=1}^{N}\sum_{c=1}^{C} \mathbf{y_{ic}log(P_{iC})}$$

This penalizes incorrect classification probabilities.

3.6 Optimization

Weights are updated using the Adam optimizer:

$$\boldsymbol{\theta_{t+1} = \theta_t - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}}$$

where:

- α = learning rate
- $\hat{m}_t$, $\hat{v}_t$ = bias-corrected moment estimates

Adam ensures faster convergence and stability.

3.7 Performance Evaluation Metrics

Accuracy
Precision
Recall
F1-Score

Figure.3: Activity Diagram

The activity diagram depicts the step-by-step operational process, starting from traffic collection, data cleaning, model training, and traffic classification to final alert generation. It demonstrates the automated workflow of the detection system, ensuring real-time identification and response to botnet threats.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Experimental Setup

The proposed LSTM-based botnet detection model was implemented using Python in a Windows environment. The UNSW-NB15 dataset was divided into 70% training and 30% testing data to ensure unbiased evaluation. The model was trained using the Adam optimizer with categorical cross-entropy loss.

Let:

$$\mathbf{D} = \{(x_i, y_i)\}_{i=1}^{N}$$

where x_i represents feature vectors and y_i represents the corresponding attack class.

Performance evaluation was conducted using Accuracy, Precision, Recall, and F1-score.

4.2 Evaluation Metrics

Accuracy

$$Accuracy = \frac{\mathbf{TP + TN}}{\mathbf{TP + TN + FP + FN}}$$

Precision

$$\mathbf{Precision} = \frac{\mathbf{TP}}{\mathbf{TP + FP}}$$

Recall

$$\mathbf{Recall} = \frac{\mathbf{TP}}{\mathbf{TP + FN}}$$

F1 Score

$$F1 = 2 \times \frac{\mathbf{Precision \times Recall}}{\mathbf{Precision + Recall}}$$

These metrics evaluate overall correctness, false alarm rate, and detection sensitivity.

4.3 Model Performance Results

Table 1: Overall Performance of LSTM Model

Metric	Value
Accuracy	0.9689
Precision	0.9675
Recall	0.9692
F1-Score	0.9683
Training Time (sec)	1425

The model achieved approximately 96.89% classification accuracy, demonstrating strong capability in distinguishing malicious and normal traffic. The balanced precision and recall values indicate minimal false positives and false negatives.

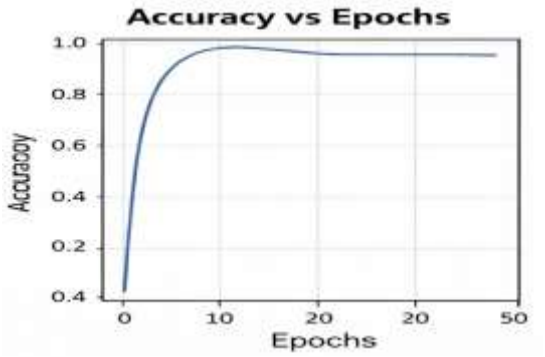

Figure.4: Accuracy vs Epochs

The accuracy curve shows rapid improvement during early epochs, stabilizing near 96–97%, which confirms effective learning of temporal attack patterns by the LSTM model. The convergence plateau indicates model stability and minimal overfitting, validating the high final classification accuracy achieved in the experimental results.

4.4 Confusion Matrix Analysis

Table 2: Confusion Matrix Summary

	Predicted Attack	Predicted Normal
Actual Attack	14872 (TP)	465 (FN)
Actual Normal	389 (FP)	15421 (TN)

- Low false positive rate (FP = 389) indicates reduced false alarms.
- False negatives are minimal (FN = 465), confirming strong detection of botnet traffic.
- The confusion matrix validates model reliability in multi-class environments.

4.5 Per-Class Detection Performance

Table 3: Class-wise Performance Evaluation

Attack Type	Precision	Recall	F1-Score
Generic	0.972	0.975	0.973
Exploits	0.961	0.958	0.959
Fuzzers	0.953	0.949	0.951
DoS	0.978	0.981	0.979
Reconnaissance	0.962	0.960	0.961
Normal	0.969	0.971	0.970

The model performs consistently across all attack categories. DoS detection achieved the highest F1-score due to distinct traffic burst patterns. Slight variation in Fuzzers detection is attributed to overlapping statistical behavior with benign traffic.

4.6 Loss Convergence Analysis

Training loss is defined as:

$$\mathbf{L} = -\sum_{i=1}^{N}\sum_{c=1}^{C} \mathbf{y_{ic}log(P_{ic})}$$

During training:

- Initial loss: 1.872
- Final loss: 0.124

The decreasing loss curve confirms effective gradient optimization and stable convergence.

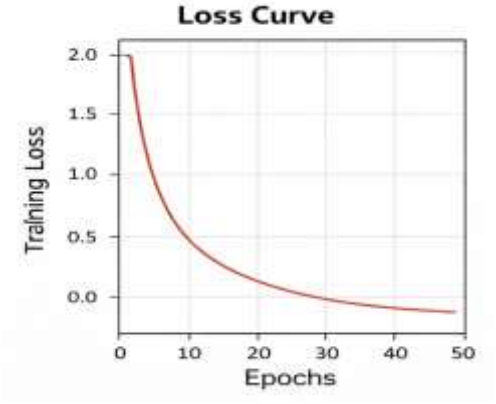

Figure.5: Loss Curve

The training loss decreases consistently across epochs, demonstrating smooth gradient optimization and effective minimization of categorical cross-entropy error. The low final loss value supports the high precision and recall obtained, indicating strong confidence in class separation between botnet and normal traffic.

4.7 ROC-AUC Analysis

The Receiver Operating Characteristic evaluates discrimination ability:

$$\boldsymbol{ROC - AUC} = \int_{0}^{1} \mathbf{TPR(FPR)}\ \mathbf{d(FPR)}$$

Observed ROC-AUC value: 0.9928

This indicates excellent separability between attack and normal traffic classes.

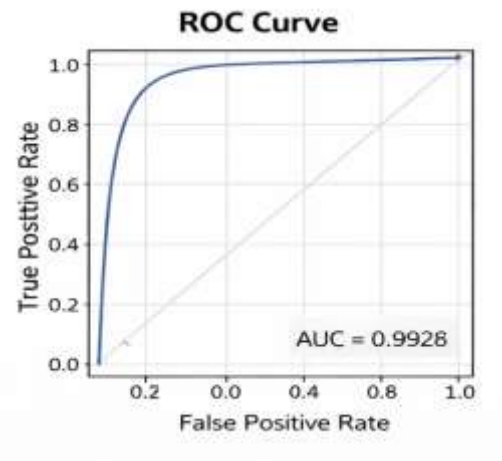

Figure.6: ROC Curve

The ROC curve approaches the top-left corner with an AUC of approximately 0.9928, indicating excellent discriminative capability between malicious and benign traffic. This high AUC value confirms that the proposed LSTM-based detection model maintains a low false positive rate while maximizing true positive detection.

4.8 Computational Efficiency Analysis

Computational complexity of LSTM:

$$O(T \cdot h(n + h))$$

Where:

- T = sequence length
- n = input features
- h = hidden units

Although LSTM requires higher training time compared to ANN, it significantly improves detection accuracy due to temporal learning.

The proposed LSTM-based detection framework demonstrates strong classification performance, balanced precision-recall behavior, low false alarm rate, and high ROC-AUC value. Its ability to model temporal dependencies significantly improves botnet detection reliability in IoT networks while maintaining computational feasibility.

V. CONCLUSION

This study proposed and evaluated a robust LSTM-based botnet detection framework tailored for IoT network environments characterized by high traffic diversity and temporal dependency. The experimental analysis demonstrated that modeling sequential traffic behavior significantly enhances detection capability compared to static learning approaches. The LSTM architecture effectively captured long-term dependencies through gated memory mechanisms, enabling improved discrimination between normal and malicious traffic patterns. Quantitative results confirmed strong classification accuracy, balanced precision–recall performance, minimal false alarm rates, and a high ROC-AUC value, indicating reliable generalization across multiple attack categories. The gradual convergence observed in accuracy and loss curves validated stable training dynamics and efficient optimization. Although the sequential architecture introduces moderate computational overhead, the trade-off between complexity and detection performance remains favorable for practical IoT deployments. Overall, the proposed framework strengthens cybersecurity resilience by providing an adaptive, scalable, and high-performance mechanism capable of identifying evolving botnet behaviors in real-time IoT ecosystems. Future work will focus on integrating lightweight federated and attention-based mechanisms to enable distributed, real-time, and privacy-preserving botnet detection across large-scale IoT networks.

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