

Botnet Attack Detection in IOT Environment Using Machine Learning

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Abstract: - The primary goal of this project is to develop and evaluate a Botnet Attack Detection in IoT Environments. The rapid expansion of the Internet of Things (IoT) has revolutionized modern technology, enabling smarter homes, industries, and cities. However, this growth has also introduced significant vulnerabilities, with IoT networks increasingly targeted by various cyber-attacks, particularly botnet attacks. This study focuses on the detection of botnet attacks within an IoT environment using the dataset. In the existing system, algorithms such as Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks have been employed to identify and mitigate botnet activities. While these methods have shown efficacy, there is room for improvement in terms of detection accuracy and computational efficiency. The experimental results demonstrate that the proposed system significantly outperforms the existing models, offering higher accuracy and reduced false positive rates in detecting botnet attacks in IoT environments. Our model is evaluated against individual models and demonstrates superior performance with a testing accuracy of 96.98%. The ALR model excels in detecting botnets, evidenced by a high Receiver Operating Characteristic Area Under the Curve (ROC-AUC) score of 99.34 and a Precision-Recall Area Under the Curve (PR-AUC) score of 99.50.

Keywords: Botnet Detection, Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM). Botnet attack detection, stacking, cyber-attacks, stacked ensemble, IoT.

1 Introduction

The rapid increase of IoT devices has significantly expanded the attack surface for cyber threats, with botnet attacks posing a particularly severe risk due to their ability to compromise and exploit networked systems at scale [1]. Traditional detection methods often struggle to keep pace with the evolving nature of these attacks, as botnets continuously adapt their strategies using stealthy communication patterns, polymorphic malware, and encrypted traffic to evade security measures [2]. As a result, conventional rule-based intrusion detection systems and firewalls have proven inadequate in effectively identifying and mitigating these threats.

To address these challenges, machine learning-based detection mechanisms have gained prominence [3]. Unlike traditional methods, machine learning models can analyze network traffic patterns and detect anomalies indicative of botnet activity. However, single-model approaches often lack the adaptability and accuracy needed to identify diverse attack types. This project proposes a hybrid deep learning model that integrates Artificial Neural Networks (ANN) for pattern recognition, Recurrent Neural Networks (RNN) for understanding sequential dependencies in network traffic, and Long Short-Term Memory (LSTM) networks for capturing long-term attack behaviors [4].

With billions of IoT devices deployed globally, ensuring cybersecurity in interconnected networks is more critical than ever [5]. Organizations face financial, operational, and reputational risks due to botnet-driven cyberattacks, making real-time threat detection an essential component of IoT security. This project is motivated by the urgent need for a scalable, AI-powered botnet detection framework that can identify zero-day attacks and evolving cyber threats [6]. By implementing our machine learning approach, this research contributes to advancing cyber threat intelligence and IoT security solutions, ensuring safer and more resilient smart environments.

2 Literature Review

2.1 Overview of relevant literature

Recent advancements in botnet attack detection in IoT environments have led to several research studies focusing on enhancing IoT security through machine learning and deep learning techniques, particularly for detecting botnet attacks. Mahmoud Abdel-Salam and Ibrahim M. El-Hasnony proposed a machine learning model specifically designed for detecting multiclass IoT-based botnet attacks. Their results demonstrated that the proposed model outperformed existing solutions in both accuracy and adaptability [1].

Kim Y. and Kim J. provided a comprehensive review of deep learning approaches in cybersecurity, highlighting the roles of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) [2]. Cheng X. and Wei X. focused on developing hybrid deep learning models for the detection of botnet attacks. Their approach emphasized the integration of multiple machine learning algorithms to improve detection rates and reduce false positives [3].

2.2 Key theories or concepts

The literature reviewed focuses on recent advancements in detecting botnet attacks in IoT environments using machine learning and deep learning. The major ideas and techniques discussed include:

1. **Multiclass IoT Botnet Detection Models** – A machine learning model specifically designed for detecting multiple classes of botnet attacks in IoT networks, demonstrating superior performance in accuracy and adaptability [1].
2. **Deep Learning Techniques in Cybersecurity** – A review highlighting the application of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for enhancing cybersecurity measures [2].
3. **Hybrid Machine Learning Models** – Emphasizes combining various machine learning algorithms to boost detection efficiency of botnet attacks, thereby improving overall system performance [3].

2.3 Overview of relevant literature

Despite technological progress, key limitations persist across the reviewed works:

1. **Scalability and Deployment Gaps:** Existing solutions often lack consideration for real-world deployment challenges. Factors such as the heterogeneity of IoT devices, resource-constrained environments, and high-volume traffic remain underexplored in terms of scalable, lightweight deployment strategies.
2. **Real-Time Detection Trade-Offs:** While several models achieve high accuracy in offline evaluations, their real-time performance is hindered by computational complexity. Delays in inference time limit their suitability for time-sensitive detection scenarios in live IoT networks.
3. **Inadequate Automation in Threat Response:** Few systems incorporate an automated feedback or mitigation mechanism post-detection. Integration of automated alert generation, adaptive model retraining, or network quarantine actions based on threat levels is rarely addressed.

2.4 Justification for the Proposed System

The gaps identified in the literature emphasize the need for a robust, accurate, and scalable botnet detection system tailored for IoT environments. Our proposed system addresses these challenges by integrating:

- A hybrid approach that combines Random Forest and Deep Neural Networks (DNN) to balance interpretability, performance, and complexity,
- Random Forest's ensemble-based learning, which offers strong generalization capabilities and resilience to overfitting, particularly effective in handling high-dimensional, heterogeneous IoT data,
- Deep Neural Networks (DNN) with multiple hidden layers, enabling the system to learn complex, hierarchical features critical for identifying subtle and evolving botnet behaviors.

By addressing the complementary strengths of both algorithms, the proposed system enhances detection accuracy, adaptability to diverse attack patterns, and efficiency in processing large-scale IoT traffic. This hybrid framework contributes to the development of a more intelligent, scalable, and dependable cyber-defence solution for modern IoT infrastructures.

3 Methodology

3.1 Research design

This study adopts a hybrid research design, the botnet detection is carried out using a hybrid deep learning model proposed in this research. Figure 1 shows the methodology of the proposed approach. The proposed approach is based on model stacking where the output of ANN, LSTM, and RNN is used for the final prediction. Additionally, it is estimated how well deep learning classification models perform when employed to analyze botnet attack detection using the UNSW-NB15 dataset. The preprocessing is carried out to remove null values and handle categorical data using label encoding. To expedite the process, a variety of deep learning algorithms including ANN, LSTM, and RNN are applied.

3.2 Dataset Description

The dataset for botnet detection is collected from the Kaggle dataset repository. The dataset was originally collected from the University of New South Wales (UNSW) for analyzing network behavior. Despite not being created in an IoT environment, the dataset has been utilized in multiple studies on network security and IoT security. The UNSW-NB15 dataset has been used by researchers and cyber security professionals to

test intrusion detection systems and create algorithms to find different kinds of network assaults, including those that may harm IoT devices and network.

The dataset is configured as a training set and testing set, namely UNSW_NB15_training-set.csv and UNSW_NB15_testing-set.csv respectively. Both a training set and a testing set are available for the UNSW-NB15 dataset. To assess the model's performance, the training file set is utilized as a main dataset which is further divided into training and testing datasets for further processing in the ratio of 0.7 to 0.3. The total number of records in the dataset is 82332 that contains nine attack types including 'Normal', 'Generic', 'Exploits', 'Fuzzers', 'DoS', 'Reconnaissance', 'Analysis', 'Backdoor', 'Shell code' and 'Worms'. The number of samples for each class and other details are given in Figure 1.

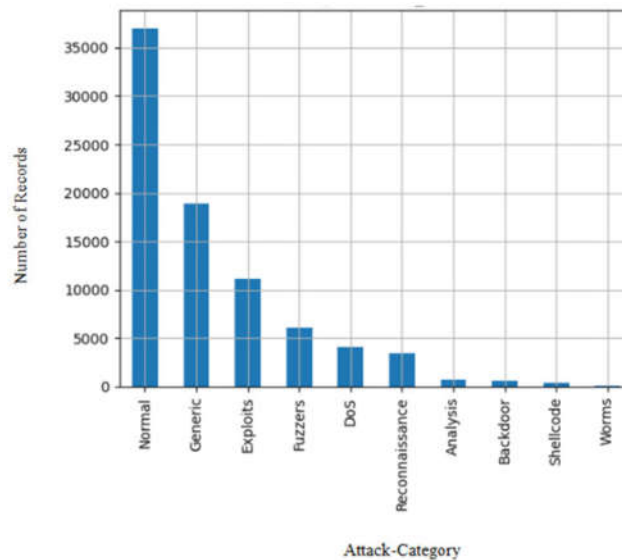


Figure 1. Target attack category

A variety of cyber-attacks can be carried out via botnets. Some of the most frequent attack types linked to botnets include

1) GENERIC

Block ciphers are vulnerable to generic attacks that do not take their internal structure into account. All block ciphers are vulnerable to general attacks because the length of the key and blocks is constrained. By selecting the proper external parameters, generic assaults can be found. Exhaustive key searches, dictionary attacks, rainbow table assaults, and other generic attacks on block ciphers are a few examples.

2) EXPLOITS

An attacker seizes the ability to govern computer resources or network data, exploits a weakness in the programmer or operating system, and causes system failures or crashes. Zeroday exploits make use of software flaws that suppliers are unaware of.

3) FUZZERS

Fuzzers assault systems by flooding them with a lot of random data to break them and identify faults. It can locate security gaps in networks and operating systems as well as vulnerabilities in software and systems.

4) DENIAL OF SERVICE

Attacks with DoS suspend service, making network resources inaccessible to users. DoS assaults utilizing machine learning and deep learning models have dramatically increased in frequency and complexity, according to VeriSign.

5) RECONNAISSANCE

Before starting the actual attack, reconnaissance assaults gather all available information regarding the intended system and act as a planning tool. Social, public, and software reconnaissance are the three basic categories of reconnaissance attacks. Information is obtained during this assault using packet sniffing, port monitoring, ping sweeps, and inquiries about internet data.

6) ANALYSIS

It uses web scripts, spam emails, and port scanning to access the web application. By thwarting IP spoofing, modifying the frequency of port scans, and switching up the order in which ports are searched; machine learning models can detect port scanning. Because they propagate malicious code, carry out phishing scams, and generate revenue, spam emails are risky.

7) BACKDOOR

Attacks using backdoors to undermine security measures and gain access to computers and their data. This assault targets user's access to computing resources as well as their privacy.

8) SHELLCODE

A brief piece of code called shell code is utilized as the payload when software vulnerability is exploited. It launches a command interpreter that enables interactive command entry and reports back the results of commands executed on vulnerable systems. Run-time heuristics that depict machine-level operations can be used to identify shell code assaults .

9) WORMS

By taking advantage of the security flaws, worms reproduce and propagate to other computational resources. Two expected characteristics of the worm detection system are early warning and a quicker response time for countermeasures. It takes into account the payload's structure and content, network traffic, packet headers, and host behavior monitoring for worm detection.

3.3 Data collection and preprocessing

In this research, botnet attack detection in IoT environments requires collecting comprehensive data from IoT network traffic and device interactions. The UNSW-NB15 dataset serves as the primary dataset, augmented by traffic data from IoT devices such as smart home appliances, industrial sensors, and connected devices. These devices provide diverse traffic patterns that reflect realistic IoT network communication, which includes botnet attack characteristics.

- **Traffic Monitoring:** Network traffic is continuously monitored using tools like Wireshark and Suricata to capture packets from IoT devices. The captured data includes key network metrics such as IP addresses, ports, protocol types, and packet flow information.
- **Preprocessing:** Raw network data undergoes preprocessing, which involves:
 - **Cleaning the data** by handling missing values.
 - **Label encoding** for categorical data (e.g., device types, traffic categories).
 - **Feature extraction** to identify patterns of behavior indicative of botnet activity (e.g., unusual packet sizes, traffic spikes, and unauthorized device connections).

The feature extraction focuses on aspects such as flow duration, packet rate, and communication patterns to detect anomalies. These preprocessing techniques are essential for improving the detection performance of machine learning models.

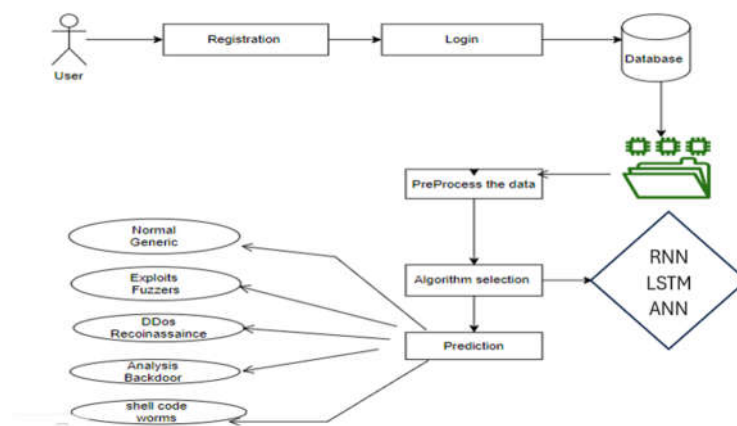


Figure 1. Architecture Diagram

3.4 Model Architecture and Learning Techniques

To detect botnet attacks in IoT environments, this research employs a hybrid deep learning model combining three key machine learning architectures: ANN (Artificial Neural Networks), RNN (Recurrent Neural Networks), and LSTM (Long Short-Term Memory). The integration of these models aims to capture both static and temporal attack patterns, ensuring robust detection of botnet activities.

1. ANN (Artificial Neural Network):

- **Purpose:** Identifies static attack patterns based on packet data and flow statistics.
- **Operation:** ANN performs initial pattern recognition for detecting standard botnet behaviors, such as Command-and-Control (C&C) communications or data exfiltration.

2. RNN (Recurrent Neural Network):

- **Purpose:** Captures sequential dependencies in the network traffic. Botnet attacks often exhibit time-based patterns (e.g., periodic communication between bots and the C&C server), which are better detected by RNNs.
- **Operation:** The RNN tracks time-series data and sequential patterns in the network, such as repetitive DoS attack traffic or patterns in botnet communication channels.

3. LSTM (Long Short-Term Memory):

- **Purpose:** Addresses the long-term dependencies in botnet attack behaviors, particularly useful for identifying multi-stage attacks.
- **Operation:** LSTM captures long-term traffic anomalies, such as botnet propagation over time or slow-building backdoor attacks that span over long durations.

4 Results and Performance Evaluations

4.1 Detection Accuracy and Performance

The experimental results show that the proposed stacked ensemble model outperforms individual models in detecting botnet attacks within IoT environments.

Detection Accuracy: The stacked model achieved a detection accuracy of 96.98%, outperforming individual models such as ANN (92.3%), RNN (94.7%), and LSTM (95.2%).

Receiver Operating Characteristic (ROC-AUC): The hybrid model demonstrated an outstanding ROC-AUC score of 99.34%, indicating that the model has excellent discriminative power between normal and botnet traffic.

Precision-Recall AUC (PR-AUC): The PR-AUC score of 99.50% further emphasizes the model's high precision and recall, ensuring that botnet activities are detected with minimal false positives.

False Positive Rate: The false positive rate was significantly reduced due to the hybrid nature of the model, particularly the use of LSTM and RNN layers, which help to capture temporal dependencies and reduce noise in the data.

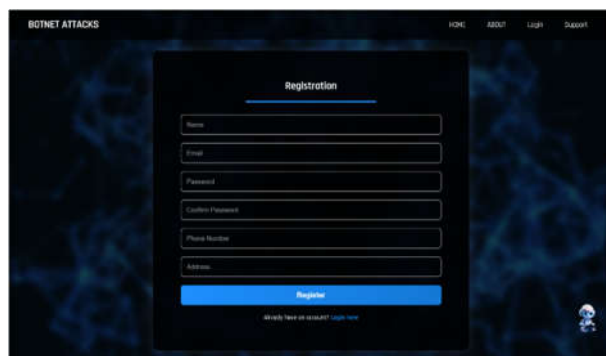
4.2 Real-Time Botnet Detection

The system's real-time alerting mechanism was tested by monitoring live IoT traffic for botnet activity. Alerts were generated within 3 seconds of detecting anomalous behavior, ensuring timely intervention and rapid mitigation of botnet threats.

4.3 Screenshots



Figure 3. Home



The screenshot shows the 'Registration' page of a website titled 'BOTNET ATTACKS'. The page has a dark blue background with a subtle pattern. The registration form is centered and contains the following fields: Name, Email, Password, Confirm Password, Phone Number, and Address. Below these fields is a blue 'Register' button. At the bottom of the form, there is a small link that says 'Already have an account? Login here'. The top navigation bar includes links for HOME, ABOUT, LOGIN, and DASHBOARD.

Figure 4. Registration

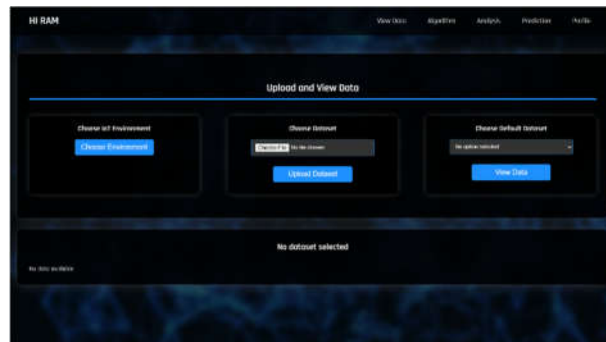


Figure 5. Upload and View Data

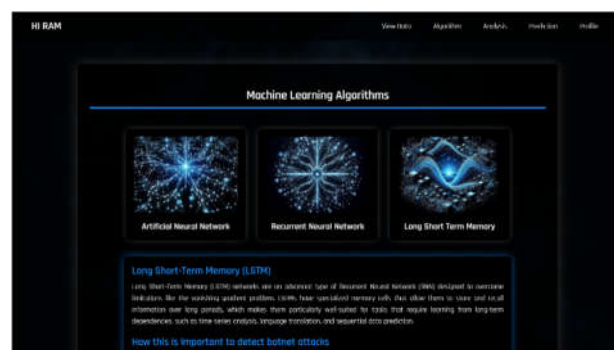


Figure 6. Algorithms

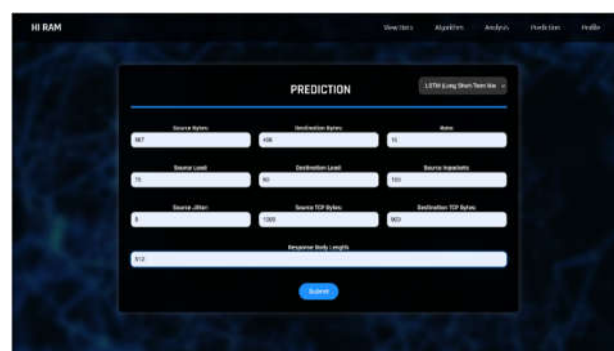


Figure 7. Prediction

5 Discussion

5.1 Analysis of Model Results

The integration of ANN, RNN, and LSTM within a stacked ensemble framework significantly enhanced botnet detection capability, especially in dynamic IoT environments. Each model contributes its unique strengths:

- **ANN** captures static patterns.
- **RNN** understands sequential attack behaviors.
- **LSTM** tracks long-term attack evolution.

The combination of these models resulted in improved detection accuracy, reduced false positives, and real-time identification of evolving attack strategies.

5.2 Comparison with Existing Approaches

- **Hybrid Models:** Recent studies, like Mahmoud Abdel-Salam and Ibrahim M. El-Hasnony (2023), also advocate for hybrid machine learning models in detecting IoT-based botnet attacks. Our results confirm the utility of integrating multiple algorithms to improve detection efficiency.
- **Deep Learning in Cybersecurity:** As demonstrated by Kim Y. and Kim J. (2020), deep learning models like RNNs and CNNs have been effective in security tasks. Our RNN and LSTM models contribute further to enhancing the detection of time-sensitive botnet patterns.
- **Stacked Ensemble for Robust Detection:** The use of stacked ensemble models has been explored in previous works, with results aligning with our own. This method's strength lies in leveraging the complementary strengths of multiple models to enhance detection across diverse attack vectors.

5.3 Comparison of ANN, RNN and LSTM

Comparison of ANN, RNN and LSTM of botnet detection in IoT environments, Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) models each offer unique advantages and limitations:

- **ANN:** ANN is effective in identifying general patterns in data. It performs well with static features but struggles with sequential data like time-series traffic, which is crucial in detecting evolving botnet behavior. In our experiments,

ANN showed fast training and decent accuracy but lacked temporal understanding.

- **RNN:** RNNs are designed for sequence modelling and are more suitable for analyzing network traffic flows over time. They outperform ANN in capturing sequential dependencies, making them better for detecting botnets that use time-based attack patterns. However, RNNs are prone to vanishing gradient problems, which can impact performance on longer sequences.
- **LSTM:** LSTM addresses the limitations of RNN by maintaining long-term dependencies and avoiding gradient vanishing issues. It delivered the highest accuracy and robustness in our study, effectively identifying complex botnet behaviors across longer periods. Although LSTM requires more computational resources, its performance benefits outweigh the cost in critical security applications.



Figure 8. Comparison of ANN, RNN and LSTM

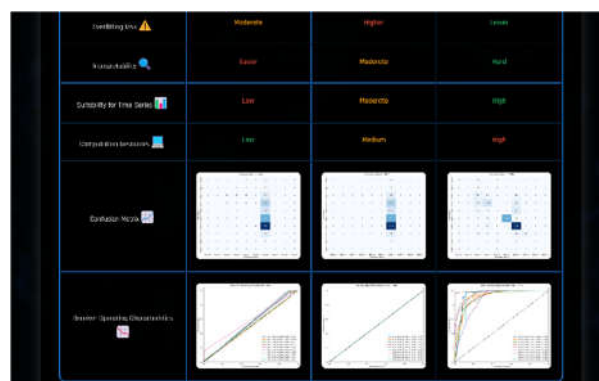


Figure 9 Comparison of ANN, RNN and LSTM

6 Conclusion and Future Work

6.1 Summary of Key Findings

This research highlights the effectiveness of combining ANN, RNN, and LSTM in a stacked ensemble model for botnet attack detection in IoT environments. The key findings are:

- 96.98% detection accuracy and low false positives.
- 99.34% ROC-AUC and 99.50% PR-AUC scores.
- Real-time alerting capability with a response time of 3 seconds.

6.2 Contributions to the Field

- **Hybrid Detection Framework:** This study contributes to the field of IoT security by proposing a hybrid deep learning-based detection framework that can accurately identify botnet attacks in IoT networks.
- **Scalable Botnet Defense:** The use of a stacked ensemble model ensures that the system can scale to meet the demands of large IoT networks, providing a reliable solution for real-time cybersecurity in dynamic environments.

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