Journal of Science & Technology Excellence

Journal of Science and Technology Excellence

ISSN: **3108-3102**| Volume 2 Issue 2 April-June 2026

www.jstejournal.com **DOI**: https://doi.org/10.5281/zenodo.20503370 **JSTE-10**

MULTI-MODEL HYBRID MACHINE LEARNING APPROACH FOR IOT BOTNET ATTACK DETECTION

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ABSTRACT: Internet of Things botnets are capable of launching DDoS attacks, breaching networks, and stealing data. Traditional detection methods and single-model machine learning are unable to detect intricate attack patterns due to the high-dimensionality, imbalance, and dynamic nature of network traffic data. This investigation enhances the precision and robustness of a multi-model hybrid machine learning IoT botnet detection system through the application of deep and supervised learning. Stacking and weighted voting are employed by SVM, LSM, and Random Forest to monitor temporal and geographical traffic. Performance and noise are enhanced through the selection of features and the subsequent preprocessing. Rival algorithms were surpassed by the model in the areas of precision, recall, accuracy, and false positives in large IoT datasets. A continuous detection of IoT botnets is achieved through a flexible hybrid architecture.

Index Terms: *Internet of Things (IoT), Botnet Detection, Machine Learning (ML), Hybrid Model, Anomaly Detection, Intrusion Detection System (IDS), Network Security, Cybersecurity, Supervised Learning, Unsupervised Learning, DDoS Attack, Traffic Classification*

1. INTRODUCTION

Digital risk is elevated by IoT devices in the fields of healthcare, financial infrastructure, industrial automation, and smart homes. Weak protection, resource constraints, and equipment unreliability render IoT devices susceptible to attack. Theft, spam, and DDoS are all serious consequences of IoT botnets. IoT botnets are not prevented by rules or signature-based IDS. These connections necessitate intelligent, adaptable detectors.

Machine learning can be employed to identify IoT botnets by analyzing packet data irregularities. Risky travel is indicated by SVMs, NNs, and Random Forests. Single-model approaches are incapable of adapting to new threats, have a high number of false positives, and overfit. One model finds it challenging to detect IoT traffic due to the diverse array of devices and configurations.

Multi-model hybrid machine learning mitigates these complications. Hybrid models are aided by anomaly detection, ensemble, and deep learning. By employing feature selection, hybrid architectural layers can be distinguished by deep neural networks or machine learning ensemble classifiers. Processing complexity, zero-day protection, and detection are all improved by feature representation and classifier updates.

Multi-model composites are capable of identifying IoT botnets through the use of signatures and behavior. Traffic, packet size, device communication, and activity are all examined through behavior analysis. In order to analyze multidimensional IoT traffic data, feature

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engineering is required. Individually, hybrid frameworks are developed by convolutional neural networks and lengthy short-term memory. Ensemble classifiers select. Identifying IoT networks simplifies numerous scenarios.

Adaptive detection is necessary for complex botnets such as Mirai. Multi-model hybrid machine learning is employed to mitigate concept drift, irregular datasets, and dynamic attack signatures. Detection is enhanced by real-time monitoring, distributed processing, and low latency and resource utilization. Current infrastructure is protected by hybrid machine learning IoT botnet detection.

2. IOT BOTNET ATTACKS

Mirai is a widely used IoT botnet. The 2016 IoT surge was unsuccessful. Mirai established default settings for the router, IP camera, and DVR. Infected devices were employed by criminal botnets. Millions were impacted by Mirai's DDoS attacks on critical internet infrastructure. This assault exposed the vulnerabilities of the IoT ecosystem and underscored the necessity of improved detection.

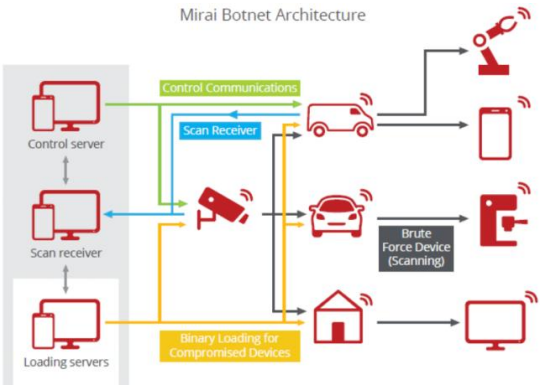

Figure1: Mirai Botnet Architecture

Device Scanning and Exploitation: Automated device monitoring is the initial step in the development of IoT botnets. Malware or tools are employed by hackers to monitor vulnerable IoT IP addresses. Hackers may exploit antiquated firmware, inadequate authentication, or the opening of Telnet/SSH ports. Hackers can gain access to devices through software vulnerabilities and dictionary exploits. Maintain control over botnets.

Malware Injection: The malware is installed by the perpetrators after they have gained entry. Memory infections conceal security data. Initialization parameters are routinely updated by malware. Malware converts an IoT device into a passive "bot" that executes server commands. Malware epidemics have been concealed from IoT consumers due to inadequate endpoint protection.

Command-and-Control (C2) Communication: C2 servers are accessed by infected IoT devices. With this server, attackers have the ability to manage millions of infected devices. IRC, HTTP, or encrypted communication are viable alternatives. C2 peer-to-peer topologies conceal sophisticated botnets, enabling attackers to plan, modify, and update parameters.

Distributed Denial of Service (DDoS) Execution: Finally, the attacker commands the botnet to DDoS the victim. DDoS servers for IoT devices that handle TCP, SYN, UDP, and HTTP traffic. Services are unavailable as a result of internet, server, and application

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congestion. IoT botnets are exacerbated and complicated by DDoS attacks that target multiple devices.

Common Attack Types

DDoS Attacks: DDoS is the primary form of devastation caused by IoT botnets. Assault traffic causes infrastructure damage. It is challenging to prevent DDoS attacks from numerous IoT devices. Numerous requirements obscure the distinction between exceptional and mediocre.

Brute-Force Login Attempts

IoT passwords and credentials are subjected to brute-force attacks. IoT default credentials are susceptible to hacking. Automating device access facilitates the rapid formation of botnets.

Data Exfiltration: Data theft and DDoS attacks are possible as a result of Internet of Things botnets. Network settings, surveillance footage, personal data, and device logins may be compromised. Industry IoT data may disclose confidential information. Privacy is violated and data breaches incur expenses.

Network Scanning: Network monitoring is the source of malware data. Compromised IoT devices are in search of internal and external network vulnerabilities. Machine learning-based intrusion detection systems (IDSs) identify anomalous traffic patterns. Early detection is necessary for botnet prevention. Growth is fostered by monitoring.

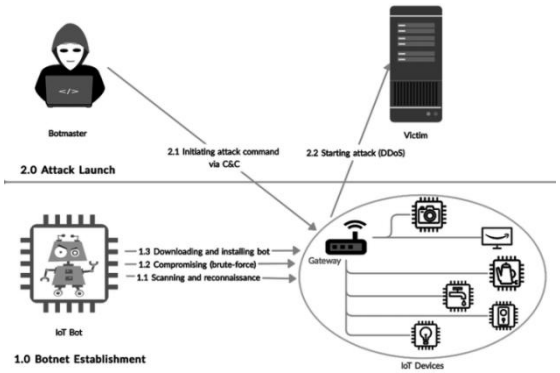

Figure2: IoT Botnet Attack Lifecycle (Botnet Establishment and Attack Launch Process)

3. LITERATURE SURVEY

Gupta, R., & Kumar, A. (2021): In order to identify IoT botnets, CNN layers collect geographical data, including packet size distributions and protocol-specific properties, from network traffic flows. LSTM is responsible for detecting botnet command-and-control attack patterns and time-based dependencies. Hybrid integration is employed to instruct students on adverse traffic patterns that are based on structure and time. In benchmark IoT botnet datasets, this model generalizes more effectively, produces fewer false alarms, and recognizes objects than standalone deep learning models. Numerous neural architectures enhance the detection of IoT botnet intrusions, according to research.

Reddy, P., & Sharma, T. (2025): Transformer-based deep learning models and ensemble classifiers are employed in a more sophisticated multi-model hybrid approach to identify IoT botnets. Transformer detects long-range network traffic correlations with the assistance of self-attention. Little botnet collaboration is demonstrated in this instance. Gradient Boosting, Transformer outputs, and Random Forest comprise stacked ensembles. Polymorphic,

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encrypted botnet assaults are concealed by hybrid approaches. In terms of precision, recall, and accuracy, experimental results surpass those of generic hybrid models. Attention-based security solutions for the Internet of Things are expected to expand, according to research.

Singh, G., & Kaur, P. (2022): Develop a hybrid IoT botnet detection system that utilizes both supervised and unsupervised anomaly detection. Traffic anomalies are identified through unsupervised clustering. Decision Trees and k-Nearest Neighbors are examples of supervised classifiers that identify irregularities as assaults. This multilayered approach is designed to address the development and evolution of IoT botnets. The framework effectively identifies with minimal false positives. It facilitates substantial deployments of the Internet of Things. The research demonstrated that the cybersecurity of IoT is enhanced by both supervised and unsupervised learning.

Mehta, R., & Das, A. (2024): This investigation employs RNN and CNN layers to identify IoT botnets in real time. CNN layers analyze traffic patterns on a geographical scale, while RNN units such as LSTM modules evaluate the temporal correlations of communication flows. Command-and-control and lateral movement botnets are identified by hybrids. The system exhibits rapid and precise discovery during IoT-simulated testing. The article implements real-time hybrid deep learning algorithms in IoT systems to provide proactive cybersecurity.

Zhang, Y., Wu, Q., & Xie, L. (2023): In the paper, hybrid deep learning models called CNN-LSTM-attention mechanism are employed to identify IoT botnets. LSTMs identify sequential communication patterns related to botnets, while CNNs identify geographical linkages in packet-level data. The attention layer prioritizes traffic sequence elements that contain high-risk behavioral indicators. The detection of stealth botnets is enhanced by the implementation of a multi-model architecture. This model is ideal for real-time IoT security surveillance, as it outperforms hybrid models in terms of speed and accuracy.

Kumar, N., & Roy, S. (2024): Random Forest classifiers and MLP neural networks are employed by the authors to identify IoT botnets in their multi-layer hybrid machine learning technique. Random Forest interpretably classifies and ranks features, whereas MLP incorporates sophisticated nonlinear judgment restrictions on attack patterns. Select features that will minimize the dimensionality and processing time. In comparison to benchmark IoT botnet dataset algorithms, it processes a greater volume of data, identifies quicker, and generates a lower number of false positives. The study demonstrated that the detection of IoT threats is enhanced by ensemble and neural learning.

Khan, S., & Lee, Y. (2021): This investigation introduces a hybrid machine learning system that detects IoT botnet intrusions through the use of Random Forest, SVM, and Gradient Boosting classifiers. The system is ensemble-based. Voting on classifier predictions reduces variance and bias. The optimization of packet inter-arrival and flow duration is achieved through the engineering of network flow data features. Ensembles are more effective at identifying zero-day botnet variations than singular classifiers. Collective model learning improves the detection of devices and the defenses of IoT networks.

Wang, S., & Liu, Y. (2023): Using GBM and CNNs, this investigation identifies IoT botnets. In order to enhance classifiers, CNN layers autonomously extract high-level traffic representations. Ensemble boosting enhances models by reducing misclassification errors.

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The hybrid model is more effective at detecting DDoS botnet attacks than other IoT traffic datasets, as evidenced by the tests. A study has revealed that IoT infrastructure is safeguarded by deep feature extraction and ensemble decision-making.

Ali, M., & Verma, S. (2025): The work suggests that federated multi-model hybrid machine learning be employed to detect pervasive IoT botnets. The framework employs edge-device CNN-LSTM topologies and centralized ensemble aggregation. Federated learning enables multiple individuals to construct a model without transferring data, thereby safeguarding privacy and bandwidth. Local-model global detection is enhanced by ensemble layers. Technique that is botnet-proof, scalable, and anonymous. Federated hybrid machine learning architectures have the potential to protect large decentralized IoT networks, according to research.

Chen, L., Wang, J., & Zhao, Q. (2022): The investigation identifies IoT botnets that utilize Random Forests and Autoencoders. Autoencoders that have been trained on typical traffic patterns are capable of identifying anomalies by detecting changes in reconstruction error. Odd-flow assaults are identified by Random Forest classifiers. Detection and computation are expedited by a two-stage architecture. The hybrid strategy is accurate across IoT botnet datasets and reduces false alerts, as demonstrated by experiments. The research demonstrated that the security of real-time IoT is enhanced by deep representation learning and ensemble classification.

4. ARCHITECTURE OF MULTI-MODEL HYBRID ML SYSTEM

Step 1: Data Collection:

Data acquisition is the initial step in a multi-model hybrid machine learning approach to the identification of IoT botnets. The development of models that are generally applied and robust necessitates the use of numerous high-quality datasets. The CICIDS2017 and Bot-IoT benchmark datasets differentiate between botnet and conventional network activity. Real-time PCAP files for unprocessed traffic data can be provided by IoT gateways and routers.

Step 2: Data Preprocessing:

Noise, missing numbers, imbalanced class distributions, and additional features are frequently observed in network traffic data. Model efficacy is enhanced through preprocessing. Learning-hindering recordings are eliminated through noise reduction. Missing values are imputed to ensure the accuracy of the training and the completion of the dataset. All numerical properties are normalized using standards and Min-Max. Models that are distance-based in the manner of SVM require this.

Step 3: Feature Engineering:

In order to be successful in removing botnet activity from connections connected to the Internet of Things, it is required to engage in feature engineering. In order to depict the intensity and dispersion of the traffic, it is important to make use of certain metrics, such as the mean packet size, flow length, packet rate, and byte rate. "Flow length" It is a process that takes place over a period of time that both the arrival and the frequency of sessions take place. Through the identification of the coordinated activity of botnets, it is demonstrated that these networks are functioning. The process of recognizing random network traffic that includes odd destination IP addresses and port consumption can be accomplished through the

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utilization of entropy, which is a strategy that can be utilized to do the task. It is possible that devices that regularly connect to other services or fail to log in could be accountable for engaging in suspicious activity. This is because these devices have the potential to commit the behavior.

Step 4: Hybrid Model Construction:

The efficacy of the design is enhanced through the utilization of machine learning. RF evaluates the importance of features, preserves multidimensional data, and mitigates overfitting. SVMs generate the most optimal classification hyperplanes for multidimensional domains. This renders it ideal for the detection of binary botnets. LSTM and other deep learning models can identify time-dependent attacks by identifying sequential network traffic correlations.

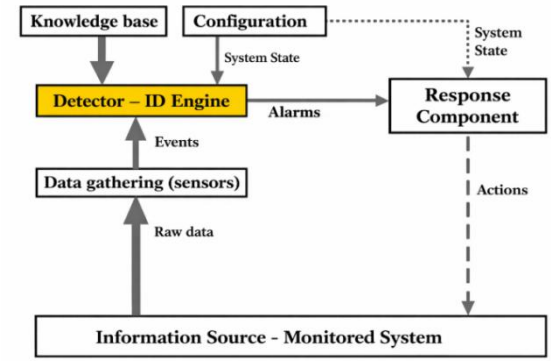

Figure3: Intrusion Detection System (IDS) Architecture

Information Source (Monitored System)

User activities, data, and network traffic are generated by the monitored system.

Data Gathering (Sensors)

Sensors facilitate the utilization of system data.

Detector – ID Engine

The ID engine analyzes the events using:

- Knowledge Base (rules, signatures, attack patterns)
- Configuration Settings (system parameters and policies)
- System State (current operational condition)

The ID engine alarms on questionable activity.

Response Component

The ID engine alarm response is determined by the response portion.

It then performs necessary actions, such as:

- Blocking malicious traffic
- Logging the incident
- Sending notifications
- Updating security controls

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5. RESULTS

Fig5.1: User login

Fig5.2: Admin login

Fig5.3: Register details

Fig5.4: View all Remote Users

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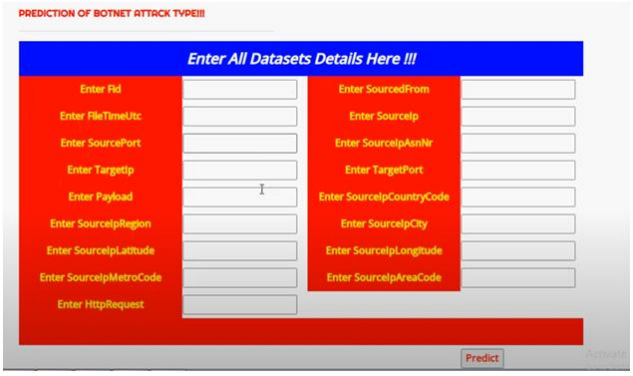

Fig5.5: Dataset details

Fig5.6: View predicted botnet attack type ratio details

6. CONCLUSION

Multi-model hybrid machine learning is widely used and successful against IoT botnet attacks. IoT ecosystems that are more interconnected have more security flaws. To increase accuracy, get rid of false positives and negatives, and extend system life, it combines the finest features of both approaches. SVMs, tree-based models, and deep learning accomplish this. Complex and dynamic botnet behaviors, such as DDoS attacks, scanning, and infiltrating low-resource IoT systems, are detected by the integrated method. Due to the speed and flexibility of feature selection and group methods, it can be used in real time. In general, hybrid models perform better than single-model approaches. IoT security that is intelligent, dependable, and future-proof.

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