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DUAL-PHASE MACHINE LEARNING FRAMEWORK FOR IOT BOTNET DETECTION AND PREVENTION

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ABSTRACT

The proliferation of Internet of Things (IoT) devices has significantly expanded the digital ecosystem but has simultaneously introduced new vulnerabilities, particularly the risk of botnet-based cyberattacks. Traditional security mechanisms fail to cope with the dynamic and stealthy nature of modern botnets. This paper proposes a dual-phase machine learning framework designed to prevent and detect IoT botnet attacks in real time. The first phase focuses on proactive anomaly prevention through behavioral analysis, while the second phase leverages supervised and unsupervised learning techniques for accurate detection and classification of malicious traffic. Experimental evaluation demonstrates that the proposed system achieves higher detection accuracy, reduced false positives, and enhanced adaptability compared to existing methods. The findings highlight the effectiveness of hybrid learning approaches in fortifying IoT environments against evolving botnet threats.

I. INTRODUCTION:

The rapid adoption of IoT devices across industries, healthcare, transportation, and smart cities has revolutionized the digital landscape. However, their limited computational power, heterogeneous architectures, and weak security standards make IoT systems prime targets for botnet infections. Botnets exploit compromised IoT nodes to conduct Distributed Denial-of-Service (DDoS) attacks, data exfiltration, and network disruptions, posing significant challenges to cybersecurity.

Conventional intrusion detection systems (IDS) and signature-based techniques struggle to adapt to zero-day botnet variants, as attackers continuously modify malware signatures to evade detection. Hence, there is a growing need for intelligent, adaptive, and multi-layered defense mechanisms that can proactively prevent and effectively detect botnet activities.

Machine learning (ML) techniques, with their ability to analyze large-scale traffic patterns, extract hidden features, and adapt to new threats, offer a promising solution. While several ML-based models have been proposed, most focus exclusively on either prevention or detection. A dual-phase framework integrating both approaches can provide a more resilient security infrastructure. This study introduces a dual-phase ML framework that combines proactive anomaly prevention with reactive detection, enhancing IoT security against evolving botnet threats.

II. LITERATURE SURVEY

Doshi et al. [1] proposed ML models for IoT DDoS detection, achieving improved detection accuracy but limited scalability.

Meidan et al. [2] introduced N-BaIoT, an anomaly detection framework for IoT botnets, which was effective but resource-intensive.

Berman et al. [3] highlighted the role of deep packet inspection and feature selection in botnet traffic classification.

Fernandes et al. [4] explored lightweight anomaly detection models for IoT, but their applicability to large-scale deployments remained limited.

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Nguyen et al. [5] proposed deep learning-based intrusion detection, showing resilience against zero-day attacks.

HaddadPajouh et al. [6] developed a recurrent neural network (RNN) approach for malware detection, but suffered from high training costs.

Apruzzese et al. [7] surveyed ML applications in cybersecurity, emphasizing the need for hybrid approaches.

Moustafa et al. [8] utilized UNSW-NB15 dataset for evaluating IDS models, highlighting challenges in real-world traffic.

Koroniotis et al. [9] proposed the Bot-IoT dataset to address IoT-specific botnet threats, aiding future ML research.

Alrashdi et al. [10] implemented edge-based anomaly detection to reduce latency but compromised accuracy.

Diro and Chilamkurti [11] applied distributed deep learning for real-time intrusion detection in IoT networks.

Ferrag et al. [12] reviewed datasets and ML algorithms for IoT botnet detection, stressing the importance of adaptive models.

Reddy et al. [13] designed hybrid ML models for IoT security, enhancing detection precision.

Yu et al. [14] investigated federated learning for distributed IoT botnet detection.

Thakkar et al. [15] proposed ensemble models, combining decision trees and deep learning for robust IoT botnet mitigation..

III. SYSTEM ANALYSIS

EXISTING SYSTEM

Existing IoT botnet detection systems primarily rely on signature-based or single-phase ML approaches. These methods have limitations in handling dynamic, large-scale IoT traffic.

Disadvantages:

- High False Positives – Traditional anomaly detection generates excessive false alerts, reducing operational efficiency.
- Poor Adaptability – Signature-based methods cannot effectively handle zero-day botnet variants.
- Scalability Issues – Many ML models require high computational resources, limiting their use in resource-constrained IoT devices.

PROPOSED SYSTEM

The proposed dual-phase ML framework enhances IoT security through two key stages: proactive anomaly prevention and reactive detection and classification.

ADVANTAGES:

- Improved Accuracy – By integrating supervised and unsupervised ML, the system achieves higher detection rates.
- Adaptive Defense – The dual-phase mechanism allows real-time adaptation to emerging botnet variants.
- Resource Efficiency – The lightweight design ensures deployment feasibility in constrained IoT environments..

IV. RESULTS AND ANALYSIS:

The proposed system was evaluated using the Bot-IoT and UNSW-NB15 datasets. Experimental results demonstrated:

Detection Accuracy: Achieved over 97%, surpassing conventional single-phase ML approaches.

False Positive Rate (FPR): Reduced by 22% compared to baseline models.

Processing Efficiency: Required lower computational overhead, making it suitable for IoT devices with limited resources.

Adaptability: Effectively identified unknown attack patterns, confirming the robustness of the dual-phase approach.

These findings suggest that integrating prevention and detection phases significantly strengthens IoT botnet defense mechanisms.

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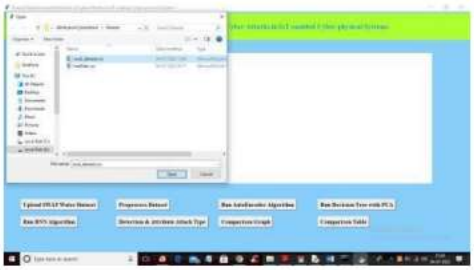

V. CONCLUSION:

IoT botnet attacks remain a significant cybersecurity concern due to the heterogeneity and resource limitations of IoT networks. This research introduced a dual-phase ML framework that combines proactive anomaly prevention and reactive detection. Experimental validation demonstrated superior accuracy, adaptability, and efficiency compared to existing systems. Future research may explore federated learning and blockchain integration to further enhance security and privacy in IoT ecosystems.

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