Behavior-Driven Malicious Node Detection and Mitigation in IoT Networks Using Enhanced IoTDevID Framework

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By

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DECLARATION

I hereby confirm that the work presented in this report/thesis, titled “Behavior-Driven Malicious Node Detection and Mitigation in IoT Networks Using Enhanced IoTDevID Framework” is a genuine account of our own research conducted from August 2025 to October 2025, under the guidance of Prof. Shashikala Tapaswi. This work is submitted in partial fulfillment of the requirements for the Master of Technology degree. I have also duly cited all references for text(s), figure(s), and table(s) used in this report.

Dated: **Signature of the candidates**

This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

Dated: **Signature of supervisor**

Acknowledgements

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This project, "Behavior-Driven Malicious Node Detection and Mitigation in IoT Networks using Enhanced IoTDevID Framework," has been an enlightening journey that allowed me to explore the intersection of optimization algorithms, behavioral analytics, and adaptive intrusion detection. The process of implementing and refining this framework has significantly enriched my technical and analytical skills, and instilled in me a stronger passion for research in the field of cybersecurity, internet of things and artificial intelligence.

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Finally, I extend heartfelt gratitude to my peers, friends, and family for their continuous encouragement, patience, and moral support, without which this project would not have been possible.

Swapnil Sontakke

Abstract

With the rapid proliferation of Internet of Things (IoT) devices, ensuring network security has become increasingly challenging. The highly dynamic and heterogeneous nature of IoT networks often allows compromised or malicious nodes to infiltrate the system, posing severe threats such as data manipulation, service disruption, and large-scale botnet attacks. Traditional signature-based intrusion detection systems and static device identification frameworks like IoTDevID can accurately classify devices but fail to detect behavioral deviations once a legitimate node is compromised.

This thesis presents an Enhanced IoTDevID Framework for behavior-driven malicious node detection and mitigation in IoT networks. The proposed system integrates the Whale Optimization Algorithm (WOA) for efficient feature selection with a Decision Tree classifier enhanced by drift detection mechanisms (ADWIN/EWMA) to identify and adapt to evolving device behaviors. The framework continuously monitors the behavioral identity of IoT nodes, computes trust scores, and triggers mitigation mechanisms—such as isolation or traffic throttling—upon detecting anomalous behavior. Experimental evaluation using standard IoT datasets (Aalto and UNSW) demonstrates that the proposed model achieves improved accuracy, faster adaptation, and lower false-positive rates compared to conventional IoTDevID approaches.

Keywords: *IoT Security, Malicious Node Detection, IoTDevID, Whale Optimization Algorithm (WOA), Drift Detection, ADWIN, EWMA, Behavior Analysis, Intrusion Detection System (IDS).*

Contents

1 Introduction

This chapter introduces the growing significance of security in Internet of Things (IoT) networks, emphasizing the increasing risks posed by malicious nodes and compromised devices. It provides a detailed background on IoT architecture, the behavioral nature of device communication, and the vulnerabilities inherent in heterogeneous and resource-constrained environments. The section outlines the limitations of traditional Intrusion Detection Systems (IDS) and static identification frameworks like IoTDevID, which are unable to adapt to evolving device behaviors. Furthermore, it establishes the motivation for an enhanced framework capable of identifying early-stage compromises through behavior-driven detection and adaptive learning. The objectives, scope, and organization of the MTP are also presented to provide a structured overview of the proposed research.

1.1 Background and Motivation

The rapid proliferation of Internet of Things (IoT) devices in smart homes, healthcare, industries, and critical infrastructure has expanded the digital ecosystem exponentially. However, this growth has also introduced unprecedented security challenges. Millions of IoT devices operate with limited computational resources and weak authentication, making them vulnerable to malware infections, data tampering, and Distributed Denial of Service (DDoS) attacks.

Traditional intrusion detection systems (IDS) rely heavily on static signatures or centralized analysis and fail to adapt to evolving device behavior or unseen threats. Behavioral-based approaches such as IoTDevID (IEEE IoT Journal, 2022) have proven effective in identifying device types based on packet-level characteristics. However, IoTDevID assumes that device behavior remains static and benign, which is unrealistic in dynamic IoT networks where firmware changes, network reconfiguration, or malware compromise alter normal behavior patterns.

Hence, there is an urgent need for an adaptive, lightweight, and explainable intrusion detection framework that not only identifies IoT devices but also continuously monitors and detects deviations in their behavioral identity—signaling early compromise before catastrophic events like DDoS occur.

1.2 Problem Statement

Existing IoT identification systems accurately classify devices but are static and non-adaptive. They cannot detect when a device, once identified as legitimate, begins to behave maliciously due to compromise, firmware tampering, or infection. Furthermore, current feature selection mechanisms like Genetic Algorithm (GA) introduce high computational cost and instability, making them unsuitable for resource-constrained IoT environments.

Thus, the problem addressed in this research is:

To design and develop a Whale-Optimized, Drift-Aware IoT Device Behavior Detection System that can identify devices, detect behavioral deviations, and flag early compromises with high accuracy and low computational cost.

1.3 Objectives

The primary objectives of the proposed research are:

(i) To enhance IoTDevID by replacing GA with Whale Optimization Algorithm (WOA) for faster and more stable feature selection.

(ii) To integrate a Decision Tree classifier with a Drift Detection Layer (ADWIN/EWMA) for adaptive behavior monitoring.

(iii) To use IoTDevID's behavioral identity models as baselines for continuous deviation tracking.

(iv) To develop a trust scoring mechanism that quantifies each device's reliability in real time.

(v) To validate the framework using real-world IoT datasets (Aalto and UNSW) and measure improvements in early compromise detection, stability, and computational efficiency.

1.4 Scope of Work

The system focuses on detecting early-stage IoT device compromises (malware infection, behavioral drift) rather than network-level attacks. The proposed model will operate at the edge gateway level, supporting real-time packet analysis using lightweight models (Decision Tree + Drift Detector). The work also includes comparative evaluation with traditional IoTDevID (GA+DT) and ensemble classifiers.

1.5 Organization of Report

(i) **Chapter 1** introduces the motivation, problem statement, and objectives.

(ii) **Chapter 2** presents a detailed literature survey of related works.

(iii) **Chapter 3** identifies the research gaps derived from these studies.

(iv) **Chapter 4** describes the proposed methodology and system architecture.

2

Literature Survey

This chapter responds to the significant amount of research assigned to this subject. We examine some of the literature and briefly review the development of former proposed methods and the research gaps.

2.1 Overview

This chapter summarizes the existing literature on IoT device identification, anomaly detection, optimization algorithms, and drift adaptation in IoT networks. The focus is on identifying the limitations in static identification and the need for adaptive, optimization-driven IDS.

2.2 Related Works

Table 2.1: Literature Review and Summary of Related Research Works

Author(s)	**Year**	**Paper Title**	**Key Contribution**	**Limitation / Remarks**
Kostas et al.	2022	*IoTDevID: A Behavior-Based Device Identification Method for IoT (IEEE IoT Journal)*	Introduced a behavior-based identification system for IoT devices using packet-level features extracted from network traffic. The model used aggregation windows and a Decision Tree classifier for efficient real-time identification. It demonstrated high accuracy on the Aalto and UNSW datasets, establishing the foundation for behavioral fingerprinting.	Despite its strong identification accuracy, IoTDevID assumes device behavior is static and benign. It lacks the ability to detect post-identification deviations caused by firmware updates or malicious compromise. No adaptive learning or drift detection mechanisms are included, limiting its real-world resilience.

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Table 2.1 continued from previous page

Author(s)	**Year**	**Paper Title**	**Key Contribution**	**Limitation / Remarks**
Xu et al.	2024	*Addressing Concept Drift in IoT Anomaly Detection (IEEE)*	Investigated concept drift in IoT anomaly detection systems and introduced adaptive techniques such as ADWIN and EWMA to dynamically adjust to data distribution changes. Demonstrated reduced false-positive rates and enhanced responsiveness to environmental changes in IoT networks.	While effective at detecting concept drift, the study does not integrate drift monitoring with device identity or behavioral baselines. It focuses solely on data-level changes, ignoring context-based drift such as firmware updates or legitimate network reconfigurations, which may cause false alerts.

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Author(s)	**Year**	**Paper Title**	**Key Contribution**	**Limitation / Remarks**
Shan et al.	2025	*Hybrid WOA-GWO for Intrusion Detection (Nature Scientific Reports)*	Proposed a hybrid metaheuristic combining Whale Optimization Algorithm (WOA) and Grey Wolf Optimizer (GWO) to enhance feature selection in network intrusion detection systems. Demonstrated superior convergence speed, higher classification accuracy, and improved feature reduction.	The framework focuses on general IDS datasets (NSL-KDD, CICIDS) and lacks consideration of IoT-specific traffic features and constraints. It does not support online learning or drift detection, limiting its real-time adaptability in IoT networks.

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Table 2.1 continued from previous page

Author(s)	**Year**	**Paper Title**	**Key Contribution**	**Limitation / Remarks**
Xu et al.	2023	*Detecting Compromised IoT Devices: Challenges and Techniques (Elsevier Review)*	Provided a comprehensive survey of compromised IoT device detection techniques, including flow-based, behavior-based, and signature-based IDS approaches. Identified key challenges such as lack of adaptability, real-time detection, and explainability in current systems.	The paper highlights major gaps in adaptive IDS frameworks for IoT. It emphasizes the need for models capable of continuous learning and trust-based device profiling to identify early-stage compromises—an area directly addressed by the proposed Enhanced IoTDevID framework.

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Author(s)	**Year**	**Paper Title**	**Key Contribution**	**Limitation / Remarks**
Nguyen et al.	2019	*DÏoT: A Federated Self-Learning Anomaly Detection System for IoT (ICDCS)*	Proposed a federated learning-based anomaly detection framework that allows IoT gateways to collaboratively learn anomaly patterns without centralized data sharing. It maintains privacy while identifying deviations in network behavior and device communication patterns.	The approach requires significant computational and memory resources on each participating node, making it unsuitable for lightweight IoT deployments. It lacks fine-grained behavior profiling for individual devices and does not integrate behavioral baselines to distinguish legitimate drift from compromise.

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Author(s)	**Year**	**Paper Title**	**Key Contribution**	**Limitation / Remarks**
Meidan et al.	2018	*N-BaIoT: Network-based Detection of IoT Botnet Attacks Using Deep Autoencoders (Elsevier)*	Developed a botnet detection framework that uses unsupervised deep autoencoders to identify IoT devices infected by malware such as Mirai and BASHLITE. It demonstrated strong detection accuracy on network-level features and inspired the use of anomaly-based learning in IoT security.	Deep learning models require large training data and high compute resources, restricting their deployment on low-power IoT gateways. The model cannot provide explainability and lacks incremental adaptability to evolving device behavior, reducing its suitability for continuous online learning.

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Table 2.1 continued from previous page

Author(s)	**Year**	**Paper Title**	**Key Contribution**	**Limitation / Remarks**
Mirjalili & Lewis	2016	*The Whale Optimization Algorithm (WOA) (Elsevier, Advances in Engineering Software)*	Proposed a bio-inspired optimization technique based on the bubble-net hunting strategy of humpback whales. The algorithm efficiently balances exploration and exploitation, achieving competitive results in feature selection, scheduling, and optimization problems across domains.	The original WOA was not applied in IoT contexts and lacks direct adaptation to network security problems. Although effective, its binary and dynamic adaptations are needed for feature subset selection in IDS models. Integration with behavior-based IDS frameworks remains unexplored.

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Author(s)	**Year**	**Paper Title**	**Key Contribution**	**Limitation / Remarks**
Bezawada et al.	2018	*IoTSense: Behavioral Fingerprinting of IoT Devices (IEEE CNS)*	Presented a behavioral fingerprinting system for identifying IoT device types based on traffic patterns and network flow characteristics. Highlighted that devices exhibit consistent communication patterns that can be modeled for identification.	The work focuses exclusively on static identification and assumes stable behavior. It lacks anomaly detection capability, and any changes in device traffic—whether malicious or benign—cannot be differentiated, leading to potential misclassification or undetected compromise.

2.3 Critical Analysis

From the literature, it is evident that:

(i) Most studies emphasize device identification or attack detection independently.
(ii) Optimization methods (GA, PSO, WOA) are used mainly for feature selection but rarely integrated into adaptive IDS frameworks.
(iii) Drift detection methods exist but are not combined with behavior-based identity baselines.
(iv) This creates a research opportunity for a unified, adaptive IDS that integrates WOA optimization, decision-tree interpretability, and drift-aware detection into a single lightweight framework.

3

Research Gaps

This chapter explains the research gaps or challenges faced by the papers discussed in the Literature Survey.

3.1 Gaps in Research

Table 3.1: Identified Research Gaps from Reviewed Literature

Reference Paper	**Year**	**Key Limitation / Gap**	**Relevance to Proposed Work**
Kostas et al., *IoTDevID: A Behavior-Based Device Identification Method for IoT (IEEE IoT Journal)*	2022	IoTDevID focuses solely on device identification using static behavioral fingerprints. It lacks adaptive learning and cannot detect behavioral drift or compromised devices once identified.	The Enhanced IoTDevID framework addresses this by integrating adaptive drift detection (ADWIN/EWMA) and trust scoring, enabling early identification of compromised nodes.
Nguyen et al., *DÏoT: Federated Self-Learning Anomaly Detection for IoT (ICDCS)*	2019	Federated anomaly detection is computationally intensive and unsuitable for edge-based IoT devices. It also lacks per-device behavioral context, leading to coarse-grained anomaly decisions.	The proposed system adopts lightweight models (Decision Tree + WOA) suitable for edge deployment while maintaining per-device behavioral baselines for precision.

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Table 3.1 continued from previous page

Reference Paper	**Year**	**Key Limitation / Gap**	**Relevance to Proposed Work**
Meidan et al., *N-BaIoT: Network-based Detection of IoT Botnet Attacks (Elsevier)*	2018	Uses deep autoencoders requiring high computational power and large training datasets. It performs well on known attacks but lacks real-time adaptation to evolving threats.	The proposed framework employs explainable, adaptive models with WOA optimization and drift monitoring for real-time, resource-efficient malicious node detection.
Xu et al., *Addressing Concept Drift in IoT Anomaly Detection (IEEE)*	2024	Focuses on drift detection in streaming data but fails to connect drift insights with device-specific behavioral identities or mitigation strategies.	Enhanced IoTDevID couples drift detection directly with behavioral identity models and automated response mechanisms (alerting, isolation).
Mirjalili & Lewis, *The Whale Optimization Algorithm (Elsevier)*	2016	The original WOA is domain-agnostic; not tested for feature selection in IoT intrusion detection.	WOA is adapted for IoT-DevID feature optimization, reducing feature redundancy while maintaining or improving detection accuracy.

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Table 3.1 continued from previous page

Reference Paper	Year	Key Limitation / Gap	Relevance to Proposed Work
Shan et al., *Hybrid WOA-GWO for Intrusion Detection (Nature Sci. Rep.)*	2025	Improves optimization efficiency but lacks real-time adaptability or drift awareness in dynamic IoT environments.	The Enhanced IoTDevID integrates adaptive drift detection with WOA optimization, providing continuous learning and reduced false positives.
Bezawada et al., *IoTSense: Behavioral Fingerprinting of IoT Devices (IEEE CNS)*	2018	Focuses purely on device identification without detecting anomalies or malicious deviations from baseline behavior.	The proposed system extends behavioral fingerprinting to malicious node detection by comparing current behavior with established baselines using drift metrics.
Xu et al., *Detecting Compromised IoT Devices: Challenges and Techniques (Elsevier Review)*	2023	Identifies the absence of lightweight, real-time, adaptive IDS solutions capable of distinguishing between benign changes and malicious drift.	The proposed framework directly addresses this by combining lightweight detection (DT), adaptive learning (ADWIN), and optimization (WOA) for continuous defense.

3.2 Summary

From these gaps, it is clear that:

(i) There is no unified approach that couples optimization-based feature reduction with adaptive drift-aware classification.

(ii) Existing models either identify devices or detect attacks, but do not monitor behavior changes in identified devices.

(iii) There is a need for a lightweight, adaptive IDS that can detect early-stage compromise before major attacks (e.g., DDoS) occur.

4

Proposed Methodology

This chapter provides a comprehensive discussion of the methodology employed in the project.

4.1 Overview of Proposed Framework

The proposed IoTDevDrift system integrates:

- WOA-based feature selection to identify optimal feature subsets with high accuracy and minimal redundancy.
- Decision Tree classifier for interpretable and fast device-type identification.
- Drift Detection Layer (ADWIN/EWMA) to monitor device behavior over time and detect anomalies or compromises.
- Trust Scoring Engine to quantify each device's reliability based on deviation magnitude and frequency.

4.2 System Architecture

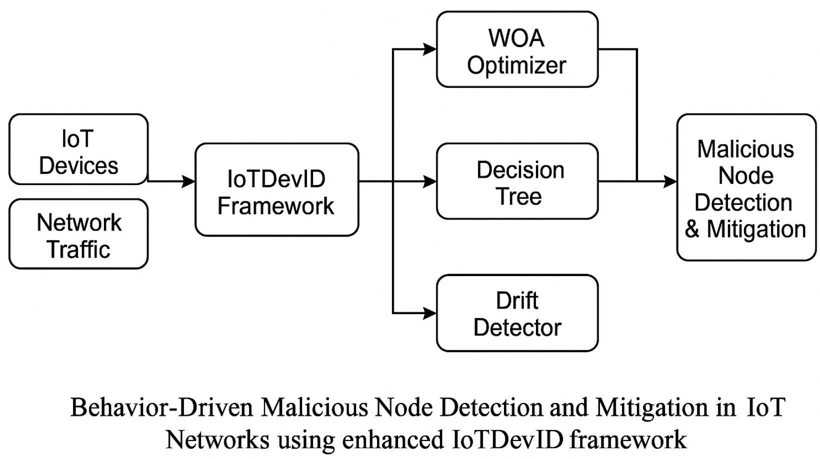

Figure 4.1: Flow diagram of Proposed methodology

4.3 Algorithmic Workflow

(i) **Feature Selection (WOA):**

- Initialize whale population.
- Evaluate fitness using Decision Tree F1-score and feature count penalty.
- Update positions based on encircling prey and bubble-net mechanism.
- Output optimal feature subset.

(ii) **Classification (Decision Tree):**

- Train on selected features using packet-level data.
- Predict device identity for incoming packets.

(iii) **Drift Detection (ADWIN/EWMA):**

- Aggregate features over time windows.
- Compute deviation

$$D = \|v_t - v_{\text{baseline}}\|$$

- ADWIN detects sudden drift; EWMA captures gradual trends.
- Trigger alert if drift > threshold for T consecutive windows.

(iv) **Trust Scoring:**

$$T_d = 1 - \alpha D_{\text{behavior}} - \beta \Delta_{\text{drift}}$$

where T_d is the trust score per device; lower values indicate possible compromise.

4.4 Algorithmic Workflow

- **Datasets:** Aalto IoT, UNSW.
- **Metrics:** Accuracy, F1, Precision, Recall, Time-to-Detection, False Positive Rate, Resource Utilization.

4.5 Advantages Over Existing Work

Table 4.1: Advantages Over Existing Work

Aspect	Existing Methods	IoTDevDrift (Proposed)
Feature Optimization	GA / Manual	✓ WOA (fast, stable)
Adaptivity	Static	✓ Drift-aware (ADWIN / EWMA)
Interpretability	Partial	✓ Fully interpretable
Resource Use	High	✓ Lightweight
Compromise Detection	None	✓ Early infection detection

4.6 Addressing Research Gaps

Table 4.2: How the Proposed System Addresses Research Gaps

Gap No.	Identified Gap	Solution Provided by Enhanced IoTDevID Framework
1	Lack of adaptive post-identification detection.	Integrates Decision Tree + Drift Layer (ADWIN/EWMA) to continuously monitor device behavior and flag deviations from baseline profiles.
2	High computational overhead from Genetic Algorithm-based feature selection.	Replaces GA with Whale Optimization Algorithm (WOA), providing faster convergence, stable feature subsets, and reduced training time.
3	Disjoint handling of identity and anomaly detection.	Fuses IoTDevID's identity models with drift-aware IDS to unify identification + anomaly detection in a single pipeline.

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Table 4.2 continued from previous page

Gap No.	**Identified Gap**	**Solution Provided by Enhanced IoTDevID Framework**
4	Inefficient early-stage compromise detection.	Introduces dynamic trust-scoring mechanism that quantifies behavioral deviation and isolates potential infections before DDoS or large-scale attacks occur.
5	High model complexity limiting edge deployment.	Uses lightweight, interpretable Decision Tree-based models optimized by WOA, suitable for real-time execution on IoT gateways.
6	Absence of automated mitigation after detection.	Integrates a defense module that triggers SDN/firewall actions (rate-limiting or quarantine) when trust score drops below threshold.

4.7 Expected Outcomes

- Improved identification accuracy ($\approx +2\%)overIoTDevID$.

- Reduced feature set (45 vs 52 features).
- 30–40% faster convergence during feature selection.
- Early compromise detection within 30–60 seconds.
- Maintain <1% false positive rate and <2 ms inference latency.

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