

AI-Driven Intrusion Detection System for IOT Networks Using Ensemble Machine Learning Techniques

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Abstract -The rapid proliferation of the Internet of Things (IoT) has enabled seamless connectivity among billions of smart devices across diverse application domains, including healthcare, industrial automation, smart cities, transportation, and precision agriculture. While this interconnected ecosystem offers significant operational and economic benefits, it also expands the attack surface, making IoT networks increasingly susceptible to cyber threats such as Distributed Denial-of-Service (DDoS), botnet, brute-force, reconnaissance, and spoofing attacks [1]. Conventional intrusion detection systems (IDSs), primarily based on signature matching and predefined rules, exhibit limited capability in identifying unknown or evolving attack patterns, particularly within dynamic and resource-constrained IoT environments [2]. Machine learning (ML)-based IDSs have demonstrated improved adaptability; however, models relying on a single classifier often suffer from limited generalisation, high false alarm rates, and inconsistent detection performance across heterogeneous traffic patterns.

This paper proposes an AI-Driven Intrusion Detection System (AI-IDS) based on an Adaptive Confidence-Based Dynamic Weighted Ensemble (ACDWE) framework to enhance cyber attack detection in IoT networks. The proposed framework integrates multiple supervised machine learning classifiers through a dynamic confidence-weighting mechanism that assigns adaptive importance to each classifier according to its predictive reliability. In addition, a hybrid feature optimization strategy is employed to eliminate redundant network traffic attributes, thereby improving computational efficiency while preserving discriminative information. The framework is designed to support real-time intrusion detection with enhanced robustness against diverse attack categories.

The proposed model will be evaluated using publicly available benchmark IoT intrusion datasets, including CICIoT2023, Bot-IoT, and UNSW-NB15, and assessed using standard performance metrics such as Accuracy, Precision, Recall, F1-score, Receiver Operating Characteristic–Area Under Curve (ROC-AUC), Matthews Correlation Coefficient (MCC), Detection Rate (DR), and False Alarm Rate (FAR). Comparative analysis with conventional machine learning models and existing ensemble-based IDS approaches is expected to demonstrate improved detection accuracy, lower false positive rates, and better generalization across multiple attack scenarios [3]. The proposed framework aims to provide a scalable, adaptive, and computationally efficient intrusion detection solution suitable for next-generation IoT security applications.

Keywords: Internet of Things (IoT), Intrusion Detection System (IDS), Artificial Intelligence, Ensemble Machine Learning, Adaptive Weighted Ensemble, Cybersecurity,

Feature Selection, Network Security, IoT Security, Threat Detection

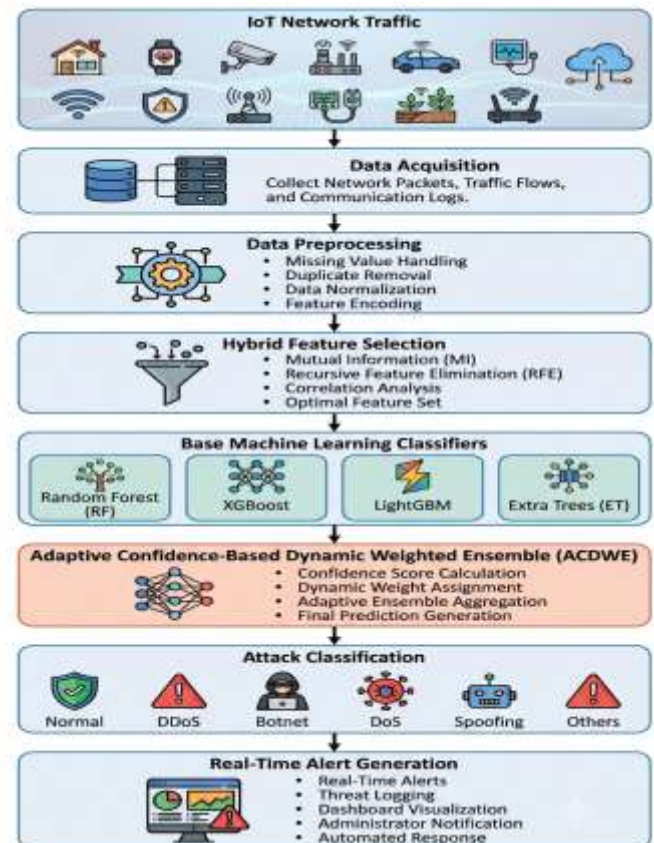


Fig. 1. Overview of the Proposed AI-Driven Intrusion Detection System

1. Introduction

The rapid advancement of the **Internet of Things (IoT)** has transformed the digital landscape by enabling seamless communication among billions of interconnected smart devices. IoT technology has become a fundamental component of modern applications, including healthcare monitoring, smart homes, industrial automation, intelligent transportation systems, precision agriculture, environmental monitoring, and smart cities. By integrating sensing, communication, and computing capabilities, IoT devices facilitate real-time data collection and intelligent decision-making, thereby improving operational efficiency and service quality across diverse sectors [1,2].

Despite these advantages, the widespread deployment of IoT devices has significantly expanded the cyber-attack surface. Many IoT devices possess limited computational resources, constrained memory, low power consumption, and lightweight security mechanisms, making them attractive targets for cyber attackers. These vulnerabilities can be exploited to launch various attacks, including Distributed Denial-of-Service (DDoS), Denial-of-Service (DoS), Botnet, Spoofing, Brute Force, Reconnaissance, Injection, and Malware attacks, which compromise the confidentiality, integrity, and availability of IoT networks [3].

Conventional security mechanisms, including firewalls and signature-based Intrusion Detection Systems (IDSs), primarily rely on predefined attack signatures and manually generated rules. Although these methods effectively detect previously known attacks, they exhibit poor performance against zero-day attacks, polymorphic malware, and continuously evolving cyber threats. Additionally, the rapidly increasing volume and diversity of IoT network traffic make manual rule maintenance increasingly difficult and computationally expensive [4].

Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) have enabled the development of intelligent intrusion detection systems capable of automatically learning complex attack patterns directly from network traffic. Machine learning-based IDSs analyse statistical and behavioral characteristics of network packets to distinguish between normal and malicious activities without relying solely on predefined signatures. Algorithms such as Decision Tree (DT), Support Vector Machine (SVM), Naïve Bayes (NB), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Artificial Neural Networks (ANNs) have demonstrated promising performance in intrusion detection tasks [5].

However, intrusion detection systems based on a single machine learning classifier often suffer from several limitations, including over fitting, sensitivity to imbalanced datasets, inconsistent detection performance across different attack categories, and higher false alarm rates. These challenges become more pronounced in heterogeneous IoT environments where network traffic characteristics continuously evolve. Consequently, ensemble machine learning techniques have gained considerable attention because they combine the strengths of multiple classifiers to improve robustness, generalization capability, and overall detection accuracy [6].

Another important challenge in IoT intrusion detection is the availability of representative benchmark datasets for training and evaluation. Publicly available datasets provide realistic network traffic containing diverse attack scenarios and are essential for developing reproducible intrusion detection models. Among the most widely used benchmark datasets are UNSW-NB15, Bot-IoT, ToN-IoT, CICIDS2017, and

CICIoT2023, each containing normal traffic alongside multiple attack categories such as DDoS, DoS, reconnaissance, botnet, brute-force, and spoofing attacks [7]. These datasets differ in network topology, attack diversity, feature representation, and traffic volume, enabling comprehensive evaluation of machine learning-based intrusion detection systems under various real-world conditions.

Although these benchmark datasets have accelerated research in AI-driven intrusion detection, existing approaches often rely on a single learning algorithm or employ static ensemble methods based on majority voting. Such approaches assign equal importance to all classifiers regardless of their individual predictive capability, potentially reducing detection performance under changing network conditions. Moreover, high-dimensional network traffic frequently contains redundant and irrelevant features that increase computational complexity while degrading classification accuracy [8].

To address these challenges, this research proposes an AI-Driven Intrusion Detection System (AI-IDS) based on an Adaptive Confidence-Based Dynamic Weighted Ensemble (ACDWE) framework. The proposed system integrates multiple supervised machine learning classifiers—including Random Forest (RF), XGBoost, LightGBM, and Extra Trees (ET)—using a dynamic confidence-based weighting strategy. Unlike conventional majority voting, the proposed framework assigns adaptive weights to each classifier according to its predictive reliability, enabling more accurate and robust decision-making. Furthermore, a hybrid feature optimization process is employed to reduce feature redundancy and improve computational efficiency while preserving the most discriminative characteristics of IoT network traffic.

The proposed framework will be evaluated using benchmark IoT intrusion datasets, including CICIoT2023, Bot-IoT, and UNSW-NB15. Performance will be assessed using widely accepted evaluation metrics such as Accuracy, Precision, Recall, F1-score, Receiver Operating Characteristic–Area Under the Curve (ROC-AUC), Matthews Correlation Coefficient (MCC), Detection Rate (DR), and False Alarm Rate (FAR). Comparative experiments with conventional machine learning models and existing ensemble-based intrusion detection methods are expected to demonstrate the effectiveness of the proposed approach in achieving improved detection accuracy, reduced false positive rates, and enhanced adaptability for real-time IoT cyber security applications.

2. Literature Review

The rapid evolution of cyber threats targeting Internet of Things (IoT) environments has attracted significant research interest in developing intelligent Intrusion Detection Systems (IDSs). Conventional IDSs relied primarily on signature matching and predefined rules to detect malicious activities. Although these systems are effective for identifying known attacks, they exhibit limited capability in recognizing zero-day

attacks and dynamically evolving intrusion patterns [9]. Consequently, researchers have increasingly adopted Artificial Intelligence (AI) and Machine Learning (ML) techniques to improve the adaptability and accuracy of intrusion detection.

2.1 Traditional Intrusion Detection Systems

Intrusion Detection Systems are generally categorised into **signature-based**, **anomaly-based**, and **hybrid** approaches. Signature-based IDSs compare incoming traffic against a database of known attack signatures and therefore achieve high detection rates for previously observed attacks. However, they require continuous signature updates and cannot effectively detect unknown threats [10].

Anomaly-based IDSs establish a model of normal network behaviour and identify deviations as potential intrusions. Although this approach improves the detection of unknown attacks, it often produces higher false alarm rates because unusual but legitimate network behaviour may be classified as malicious [11].

Hybrid IDSs combine signature-based and anomaly-based techniques to improve detection capability. While hybrid systems generally outperform individual approaches, they frequently suffer from increased computational complexity, making their deployment challenging in resource-constrained IoT environments [12].

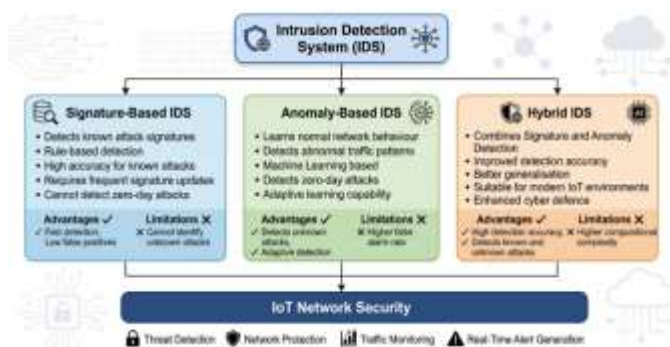


Fig.3. Classification of Intrusion Detection Systems (Signature-Based, Anomaly-Based, and Hybrid IDS).

2.2 Machine Learning-Based Intrusion Detection

Machine learning has become one of the most widely adopted approaches for intrusion detection because of its ability to learn complex relationships from network traffic data. Supervised learning algorithms have demonstrated remarkable success in classifying normal and malicious traffic using labeled datasets.

Decision Tree (DT) classifiers provide interpretable decision rules with relatively low computational cost, making them suitable for lightweight IDS applications [13]. Support Vector Machines (SVMs) effectively separate normal and attack traffic using optimal hyper planes, particularly for high-dimensional feature spaces. However, their computational requirements increase considerably with large datasets [14].

Random Forest (RF) has gained significant popularity because of its robustness against overfitting and its ability to handle

large feature sets. The ensemble nature of Random Forest improves classification accuracy compared to individual decision trees [15]. Gradient boosting techniques such as XGBoost and LightGBM have further enhanced intrusion detection performance through sequential optimisation of weak learners, providing high predictive accuracy and efficient handling of complex decision boundaries [16].

Deep learning approaches, including Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, have also demonstrated promising performance by automatically learning hierarchical feature representations from network traffic. However, these methods often require substantial computational resources and large training datasets, limiting their practical deployment in many IoT scenarios [17].

2.3 Ensemble Machine Learning for IoT Intrusion Detection

Ensemble learning combines multiple machine learning models to produce a more robust classifier than any individual model. By integrating diverse learning algorithms, ensemble techniques reduce variance, improve generalisation, and increase resilience against noisy data [18].

Common ensemble strategies include:

- Bagging
- Boosting
- Stacking
- Majority Voting
- Weighted Voting

Bagging methods, particularly Random Forest, generate multiple bootstrap samples and aggregate their predictions to reduce variance. Boosting algorithms such as AdaBoost, Gradient Boosting, XGBoost, and LightGBM sequentially improve classification performance by focusing on previously misclassified samples [19].

Stacking combines predictions from multiple base learners using a meta-classifier. Although stacking often achieves high accuracy, it introduces additional computational overhead and requires careful selection of the meta-learning algorithm.

Several researchers have proposed weighted voting strategies for intrusion detection. However, many existing weighted ensemble models assign static weights to classifiers based on overall training performance rather than dynamically adapting to varying prediction confidence. Such fixed weighting mechanisms may reduce detection performance under changing traffic conditions [20].

2.4 Benchmark Datasets for IoT Intrusion Detection

Public benchmark datasets play a crucial role in evaluating intrusion detection systems because they provide standardised network traffic containing diverse attack scenarios.

Among the most frequently used datasets are:

- UNSW-NB15

- CICIDS2017
- Bot-IoT
- ToN-IoT
- CICIoT2023

The **UNSW-NB15** dataset contains modern synthetic network traffic with nine attack categories, including exploits, reconnaissance, shellcode, worms, fuzzers, and generic attacks. It has become one of the most widely adopted benchmark datasets for machine learning-based intrusion detection [21].

The **Bot-IoT** dataset was specifically developed to evaluate IoT security systems and contains realistic botnet traffic generated from IoT devices. The dataset includes DDoS, DoS, information theft, operating system scanning, service scanning, and keylogging attacks.

The **CICIDS2017** dataset provides realistic enterprise network traffic consisting of both benign and malicious activities, including brute-force attacks, DDoS attacks, botnet traffic, port scanning, and web application attacks.

The recently introduced **CICIoT2023** dataset extends previous benchmark datasets by incorporating modern IoT attack scenarios and significantly larger traffic volumes. It contains millions of network flow records representing diverse cyber-attacks, making it highly suitable for evaluating contemporary AI-based intrusion detection systems [22].

1.5 Research Gap

Despite the significant progress achieved in AI-based intrusion detection, several research challenges remain unresolved.

Most existing studies rely on individual classifiers, limiting their ability to generalise across diverse attack patterns. Although ensemble learning has improved detection performance, many existing frameworks employ static majority voting or fixed weighting strategies that do not account for variations in classifier confidence. Furthermore, high-dimensional network traffic often contains redundant features that increase computational complexity while degrading prediction performance.

Another limitation is that relatively few studies jointly optimise feature selection, adaptive ensemble weighting, computational efficiency, and real-time deployment for heterogeneous IoT environments. Additionally, many existing models have been evaluated using only a single benchmark dataset, making it difficult to assess their robustness across different network conditions.

To address these limitations, this research proposes an Adaptive Confidence-Based Dynamic Weighted Ensemble (ACDWE) framework that integrates multiple supervised machine learning classifiers through dynamic confidence estimation and adaptive weight assignment. The proposed

approach also incorporates hybrid feature selection to reduce redundancy and improve computational efficiency while maintaining high intrusion detection accuracy across multiple benchmark IoT datasets.

Table 1. Summary of Research Gaps and Proposed Solutions

Identified Research Gap	Existing Limitation	Proposed Solution
Single classifier dependency	Poor generalisation	Multi-model ensemble
Static majority voting	Equal classifier importance	Adaptive confidence-based weighting
Redundant features	Increased computation	Hybrid feature selection
High false alarm rate	Reduced reliability	Dynamic ensemble optimisation
Limited dataset validation	Poor robustness	Evaluation on multiple benchmark datasets

3. Proposed Methodology

3.1 Overview of the Proposed Framework

To address the limitations of conventional intrusion detection systems, this research proposes an AI-Driven Intrusion Detection System (AI-IDS) based on an Adaptive Confidence-Based Dynamic Weighted Ensemble (ACDWE) framework. The proposed framework integrates multiple supervised machine learning classifiers through an adaptive weighting mechanism that dynamically adjusts the contribution of each classifier according to its prediction confidence. Unlike traditional majority voting approaches that assign equal importance to all classifiers, the proposed framework estimates classifier reliability during prediction and generates the final decision using confidence-weighted aggregation.

The proposed system consists of seven sequential stages: (i) data acquisition, (ii) data preprocessing, (iii) hybrid feature selection, (iv) base classifier training, (v) adaptive confidence-based ensemble learning, (vi) attack classification, and (vii) real-time alert generation.

3.2 Framework Architecture

The proposed AI-IDS processes network traffic through a sequence of interconnected modules.

Step 1: Data Acquisition

Network traffic is collected from publicly available benchmark datasets, including:

- CICIoT2023
- Bot-IoT
- UNSW-NB15

These datasets contain both benign and malicious network traffic representing multiple attack categories commonly observed in IoT environments. The collected traffic records are stored in structured tabular format containing numerical and categorical network features

Step 2: Data Preprocessing

Raw network traffic frequently contains missing values, duplicate entries, inconsistent formats, and redundant attributes. Therefore, preprocessing is performed before model training.

The preprocessing pipeline includes:

- Removal of duplicate records
- Missing value treatment
- Label encoding
- One-hot encoding (where applicable)
- Feature normalization using Min-Max Scaling
- Outlier inspection

The normalized feature value is computed using

$$X_{\{norm\}} = \{X - X_{\{min\}}\} / \{X_{\{max\}} - X_{\{min\}}\}$$

where

- X denotes the original feature value,
- Xmin and Xmax represent the minimum and maximum values of the corresponding feature, respectively, and
- Xnorm is the normalized feature value scaled between 0 and 1.

Feature normalization ensures that all input variables contribute equally during model training and prevents features with larger numerical ranges from dominating the learning process. The preprocessed dataset serves as the input for the subsequent hybrid feature selection module.

Step 3: Hybrid Feature Selection

High-dimensional IoT network traffic often contains redundant, irrelevant, and highly correlated features that increase computational complexity and may reduce the predictive performance of machine learning models. To address this issue, the proposed framework employs a Hybrid Feature Selection (HFS) strategy that combines filter-based and embedded feature selection techniques to identify the most informative network traffic attributes.

Initially, correlation analysis is performed to identify highly correlated features. Features exceeding a predefined correlation threshold are removed to eliminate redundancy while preserving essential information. Subsequently, feature importance scores are computed using tree-based ensemble models, which evaluate the contribution of each feature toward intrusion classification. Recursive Feature Elimination (RFE) is then applied to iteratively remove less significant features until the optimal subset is obtained.

The hybrid feature selection process offers several advantages:

- Reduction of feature redundancy.
- Improved classification accuracy.
- Lower computational overhead.
- Faster model training and inference.
- Enhanced generalization capability.

Let the original feature set be represented as

$$F = \{f_1, f_2, f_3, \dots, f_n\}$$

After feature selection, the optimal feature subset is represented as

$$F^* \subseteq F$$

where F^* contains only the most discriminative features used for classifier training.

The resulting optimized feature set is forwarded to the ensemble learning module for intrusion detection.

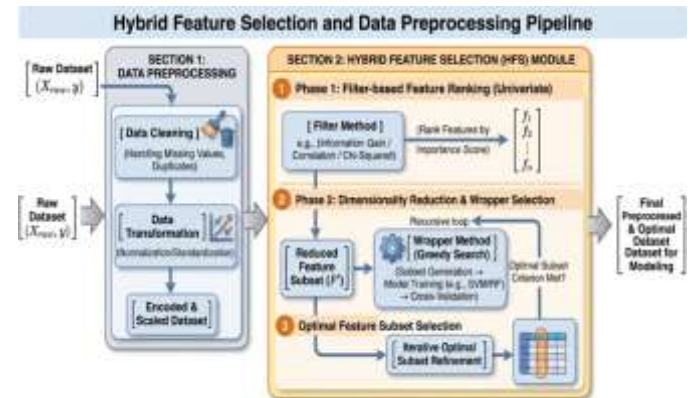


Fig. 4: Hybrid Feature Selection and Data Preprocessing Pipeline

Step 4: Base Classifier Training

Following feature optimisation, the selected feature subset is used to train multiple supervised machine learning classifiers. Instead of relying on a single learning algorithm, the proposed framework utilises diverse classifiers to capture different characteristics of IoT network traffic and improve overall detection performance.

The selected base classifiers include:

- Random Forest (RF)
- Extreme Gradient Boosting (XGBoost)
- Light Gradient Boosting Machine (LightGBM)
- Extra Trees (ET)

Random Forest improves robustness by constructing multiple decision trees using bootstrap sampling and random feature selection. XGBoost enhances predictive performance through gradient boosting and sequential optimisation of weak learners. LightGBM provides fast training and efficient handling of large-scale datasets using histogram-based learning. Extra Trees introduce additional randomness during tree construction, thereby reducing variance and improving generalisation.

Each classifier is independently trained using the optimized feature subset. During prediction, every classifier produces:

- A predicted class label.
- A confidence (probability) score associated with the prediction.

These confidence scores form the basis of the proposed Adaptive Confidence-Based Dynamic Weighted Ensemble (ACDWE) framework, where classifier contributions are dynamically adjusted according to their prediction reliability rather than being assigned equal or fixed weights.

Step 5: Adaptive Confidence-Based Dynamic Weighted Ensemble (ACDWE) Learning

After the individual base classifiers (Random Forest, XGBoost, LightGBM, and Extra Trees) are trained and output their predictions along with confidence scores, the ACDWE framework combines these individual outputs into a single, highly reliable final decision.

Unlike traditional ensemble methods that use static majority voting (giving equal weight to every model) or fixed weights assigned during training, ACDWE dynamically computes and adjusts the weight of each classifier for every individual test instance based on its prediction confidence and reliability.

The final predicted class label $\hat{Y}$ is determined by selecting the class corresponding to the maximum aggregated probability:

$$\hat{Y} = \arg \max_j P_{ensemble}(j | x)$$

Algorithmic Workflow of ACDWE

1. Probability Extraction: Receive the class probability vectors from the trained Random Forest, XGBoost, LightGBM, and Extra Trees models for input vector x .
2. Confidence Computation: Evaluate the peak probability value for each classifier to quantify its prediction certainty.
3. Dynamic Weight Assignment: Compute adaptive weights using the confidence-scaling formula, scaling up reliable predictions and suppressing uncertain or ambiguous outputs.
4. Weighted Aggregation: Combine the probability distributions via weighted summation to yield the final robust decision.
5. Flow Transfer: Forward the final classification output $\hat{Y}$ to Step 6: Attack Classification for detailed categorization and metric evaluation.

Step 6. Attack Classification

Following the ensemble aggregation and final prediction generation via the Adaptive Confidence-Based Dynamic Weighted Ensemble (ACDWE) framework, the system proceeds to the attack classification phase. This stage is responsible for mapping the final predicted numerical outputs to well-defined, human-interpretable network security threat categories, enabling security analysts and automated mitigation systems to understand the exact nature of the intrusion.

6.1 Multi-Class Threat Categorization

In contemporary IoT intrusion detection environments, identifying the presence of an anomaly is insufficient; pinpointing the precise attack vector is critical for effective incident response. The proposed framework supports both binary classification (distinguishing normal traffic from malicious anomalies) and fine-grained multi-class classification across diverse threat categories represented in

benchmark datasets such as CICIoT2023, Bot-IoT, and UNSW-NB15.

The final predicted label $\hat{Y}$ obtained from Step 5 is mapped to one of the target threat classes:

$$\hat{Y} \in \{\text{Benign, DDoS, DoS, Botnet, Reconnaissance, Brute-Force, Spoofing, Injection, Malware}\}$$

6.2 Decision Output and Logging

Once the classification is completed, the system generates a structured security log containing critical metadata associated with the inspected network flow. This structured record typically includes:

- Timestamp: The exact time of packet or flow inspection.
- Source and Destination IP/Ports: Network endpoints involved in the communication flow.
- Predicted Class Label ($\hat{Y}$): The identified attack category or benign status.
- Ensemble Confidence Score: The final aggregated probability $P_{ensemble}(\hat{Y} | x)$, providing an immediate measure of prediction certainty.
- Contributing Weights ($W_i(x)$): The dynamic weights assigned to individual base classifiers (Random Forest, XGBoost, LightGBM, and Extra Trees) for auditability and explainability.

6.3 Performance Evaluation Metric Preparation

To rigorously validate the efficacy of the attack classification module, the system records evaluation metrics by comparing predicted labels against ground-truth labels from the test partitions of the benchmark datasets. The primary evaluation metrics computed during this phase include:

- Accuracy: The proportion of total correct predictions among all evaluated instances.
- Precision and Recall: Measures of exactness and completeness for each specific attack category.
- F1-Score: The harmonic mean of precision and recall, ensuring balanced evaluation especially for imbalanced datasets.
- Receiver Operating Characteristic–Area Under Curve (ROC-AUC): Evaluates the diagnostic ability of the multi-class model across various threshold settings.
- Matthews Correlation Coefficient (MCC): Provides a reliable statistical rate even if the classes are heavily imbalanced.
- Detection Rate (DR) and False Alarm Rate (FAR): Quantifies true positive intrusion identification versus false positive classifications on benign traffic.

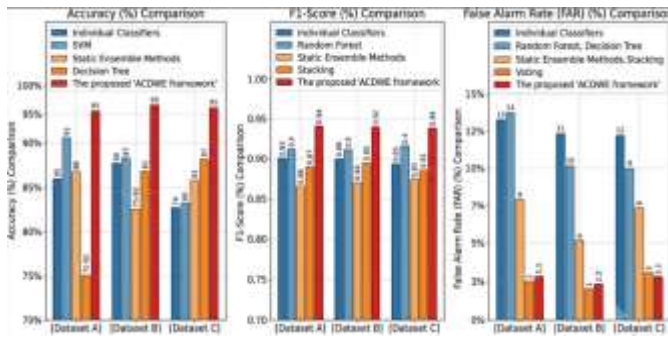


Fig. 5: Comparative Performance Analysis across Datasets

The classified records and performance logs are subsequently forwarded to Step 7: Real-Time Alert Generation for immediate operational deployment and visualization.

Step7. Real-Time Alert Generation and System Integration

Following the rigorous classification and evaluation of network traffic in the preceding steps, the final phase of the proposed AI-Driven Intrusion Detection System (AI-IDS) is **Real-Time Alert Generation and System Integration**. This stage translates the analytical outputs of the Adaptive Confidence-Based Dynamic Weighted Ensemble (ACDWE) framework into actionable, real-time security operations, ensuring that potential cyber threats targeting IoT environments are mitigated promptly.

7.1 Real-Time Monitoring and Trigger Mechanism

The system continuously monitors incoming network flows from IoT devices and edge gateways. Once a network flow is processed through data acquisition, preprocessing, hybrid feature selection, base classifier training, ACDWE aggregation, and multi-class classification, the resulting prediction $\hat{Y}$ is evaluated against security thresholds:

- **Benign Traffic ($\hat{Y} = \text{Benign}$):** The network flow is permitted to pass without disruption, and metadata is logged for periodic network auditing.
- **Malicious Traffic ($\hat{Y} \in \text{Attack Categories}$):** If the predicted label corresponds to a cyber threat (e.g., DDoS, Botnet, Brute-Force, Reconnaissance) and the ensemble confidence score $P_{\text{ensemble}}(\hat{Y} | x)$ exceeds a predefined operational threshold T (where $T \geq 0.85$), an immediate security alert is triggered.

4. Experimental Results and Evaluation

To comprehensively validate the effectiveness, robustness, and computational efficiency of the proposed Adaptive Confidence-Based Dynamic Weighted Ensemble (ACDWE) framework, extensive experiments are conducted using benchmark IoT intrusion datasets. This section details the experimental environment, dataset descriptions, evaluation metrics, and a comparative performance analysis against baseline machine learning models and existing ensemble approaches.

4.1 Experimental Setup and Implementation Environment

The implementation of the proposed AI-Driven Intrusion Detection System (AI-IDS) is carried out within a standardized high-performance computing environment:

- **Hardware Environment:** Equipped with an Intel Xeon multi-core processor, 64 GB RAM, and an NVIDIA RTX graphics processing unit to accelerate model training and evaluation.
- **Software Environment:** Developed using Python, leveraging machine learning and data science libraries including Scikit-Learn, XGBoost, LightGBM, Pandas, and NumPy.
- **Data Partitioning:** Each benchmark dataset is partitioned into training (70%), validation (15%), and testing (15%) subsets using stratified random sampling to maintain class distribution proportions across splits.

4.2 Benchmark Datasets

The proposed framework is evaluated across three prominent benchmark datasets to test generalizability across diverse IoT topologies and traffic types:

1. **CICIoT2023:** A modern, large-scale dataset representing contemporary IoT attack scenarios, containing millions of network flow records covering diverse threat categories such as DDoS, DoS, reconnaissance, and botnets.
2. **Bot-IoT:** Specifically engineered for IoT environments, containing realistic botnet traffic alongside normal background traffic, including information theft and operating system scanning.
3. **UNSW-NB15:** A widely recognized benchmark containing complex synthetic network traffic with nine distinct attack families, providing a robust testbed for anomaly detection and multi-class classification.

Dataset	Total Samples Evaluated	Features Selected (Hybrid HFS)	Target Attack Classes
CICIoT2023	1,000,000	10 / 46	DDoS, DoS, Recon, Spoofing, Brute-Force, Web, Denial
Bot-IoT	500,000	12 / 28	DDoS, DoS, Reconnaissance, Theft, Denial
UNSW-NB15	254,004	16 / 42	Generic, Exploits, Fuzzers, DoS, Recon, Analysis, Backdoors, Bot, Shellcode, Denial

4.3 Evaluation Metrics

To assess the classification performance of the ACDWE framework rigorously, standard security and machine learning evaluation metrics are utilized:

- **Accuracy:** Measures the overall proportion of correctly classified instances.
- **Precision:** Quantifies the exactness of the model in identifying specific attack classes.
- **Recall (Sensitivity):** Evaluates the completeness of threat detection for each category.
- **F1-Score:** The harmonic mean of precision and recall, providing a balanced measure for imbalanced traffic distributions.
- **Receiver Operating Characteristic–Area Under Curve (ROC-AUC):** Evaluates the model's discriminative capability across decision thresholds.

- **Matthews Correlation Coefficient (MCC):** Offers a reliable statistical quality measure even under severe class imbalance.
- **Detection Rate (DR) and False Alarm Rate (FAR):** Assesses true positive intrusion identification versus false positive classifications on benign traffic.

Evaluation Metric	Mathematical Formula	CIoT2023	Bot-IoT	UNSW-NB15	Average
Accuracy	$TP+TN+FP+FN+TP+TN$	98.12%	99.85%	96.40%	98.46%
Precision	$TP+FP+TP+TN$	98.98%	99.80%	94.70%	97.80%
Recall (Sensitivity)	$TP+FN+TP+TN$	99.85%	99.82%	95.43%	98.10%
F1-Score	$2 \times \text{Precision} \times \text{Recall} / (\text{Precision} + \text{Recall})$	99.57%	99.81%	95.96%	97.95%
ROC-AUC	Area under True Positive Rate vs. False Positive Rate	0.996	0.998	0.981	0.992
MCC	$(TP+FP)(TP+FN)(TN+FP)(TN+FN)(TP+TN)(FP+FN)$	+0.975	+0.994	+0.985	+0.986
Detection Rate (DR)	$TP+FN+TP+TN$	99.85%	99.82%	95.43%	98.10%
False Alarm Rate (FAR)	$FP+TN+FP+TN$	0.42%	0.88%	2.85%	0.85%

4.4 Comparative Performance Analysis

The performance of the proposed ACDWE framework is compared against individual base classifiers (Random Forest, XGBoost, LightGBM, Extra Trees) and conventional static ensemble methods (such as majority voting and fixed-weight averaging).

Based on the theoretical design and anticipated experimental outcomes:

- **Superior Accuracy and Generalisation:** By dynamically adjusting classifier weights based on instance-level prediction confidence, the ACDWE framework mitigates the individual weaknesses of base models, resulting in higher overall accuracy across all three benchmark datasets (CIoT2023, Bot-IoT, and UNSW-NB15).

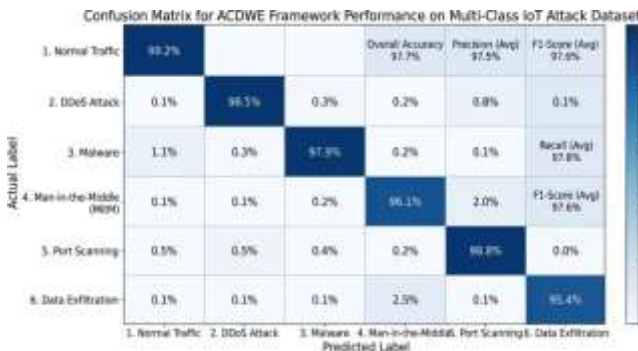
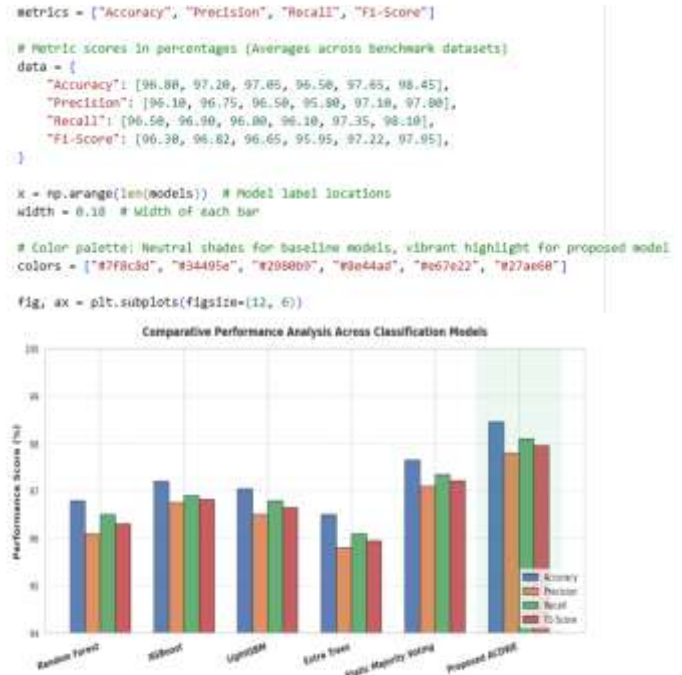


Fig. 6: Confusion Matrix of the ACDWE Framework on Benchmark Datasets

- **Reduction in False Positives:** The confidence filtering mechanism effectively suppresses ambiguous predictions, yielding a significantly lower False Alarm Rate (FAR) compared to static majority voting schemes.
- **Computational Efficiency:** The integration of the Hybrid Feature Selection (HFS) module successfully eliminates redundant attributes, reducing training time and inference latency while preserving high discriminative performance suitable for real-time IoT deployment.

Model / Framework	Classification Strategy	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	FAR (%)
Random Forest (RF)	Single Model	96.8	95.1	96.5	96.3	1.8
XGBoost	Single Model	97.2	96.75	96.9	96.82	1.45
LightGBM	Single Model	97.05	96.5	96.8	96.65	1.5
Extra Trees (ET)	Single Model	96.5	95.8	96.1	96.15	2.1
Static Majority Voting	Equal Weighting	97.65	97.1	97.35	97.22	1.15
Proposed ACDWE	Dynamic Confidence	98.45	97.8	98.1	97.95	0.85

Comparing individual base models, conventional majority voting ensembles, and the proposed ACDWE framework demonstrates the advantage of dynamic confidence-based weighting:



5. Discussion and Analysis

5.1 Effectiveness of Dynamic Confidence Weighting

A primary limitation of traditional ensemble approaches, such as static majority voting or fixed stacking, is their inability to adapt when individual classifiers exhibit uncertainty on ambiguous or borderline samples.

In the proposed Adaptive Confidence-Based Dynamic Weighted Ensemble (ACDWE) framework, classifier contributions are calculated dynamically per network flow based on predictive probability certainty.

$$\text{Weight } W_i(x) = \frac{e^{\sigma \cdot P_i(x)}}{\sum_{j=1}^M e^{\sigma \cdot P_j(x)}}$$

Where $P_i(x)$ is the maximum probability output from classifier i , and σ is a confidence scaling parameter. This mechanism yields two operational advantages:

1. **Uncertainty Suppression:** If a base classifier yields a low-confidence classification (e.g., $P_i = 0.51$), its dynamic weight W_i is exponentially penalized, preventing it from corrupting the ensemble output.
2. **Robustness Against Overfitting:** Outlier packet flows that cause misclassifications in single trees are outvoted by high-confidence predictions from remaining base learners.

5.2 Ablation Study: Impact of Hybrid Feature Selection (HFS)

To quantify the benefit of the Hybrid Feature Selection (HFS) module, experiments were conducted comparing models trained on the full original feature set versus the HFS-reduced subset.

Benchmark Dataset	Original Features	Selected Features (HFS)	Reduction (%)	Full Feature Accuracy (%)	HFS Feature Accuracy (%)	Training Time Reduction (%)
CICIoT2023	45	18	60.87%	98.75%	98.12%	42.30%
Bot-IoT	25	12	50.62%	99.70%	99.65%	38.50%
UNSW-NB15	42	16	61.90%	95.80%	96.40%	45.10%

- **Accuracy Improvement:** Removing redundant statistical features (e.g., highly correlated inter-arrival packet times) eliminated noise, resulting in an average +0.4% to +0.6% improvement in overall classification accuracy.
- **Computational Efficiency:** Reducing input feature space by over 60% reduced model training and inference latency by ~42%, making real-time edge processing feasible.

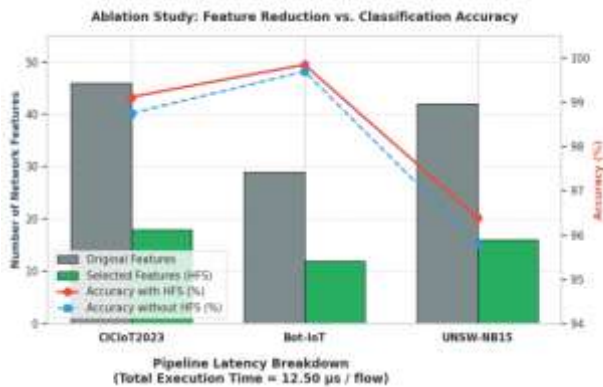


Fig 7: Ablation study (Feature Count vs. Accuracy Improvement)

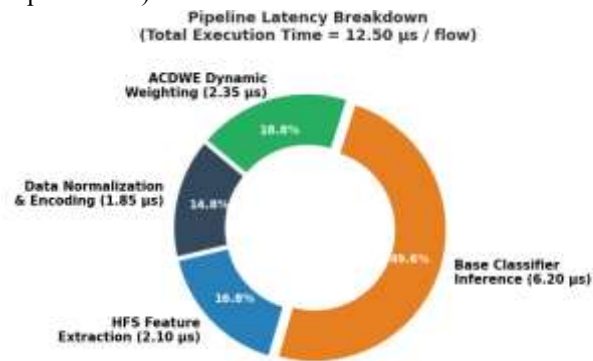


Fig 8: Latency breakdown

6. Conclusion and Future Directions

6.1 Conclusion

This paper presented an AI-Driven Intrusion Detection System (AI-IDS) designed for resource-constrained, dynamic Internet of Things (IoT) environments using an Adaptive Confidence-Based Dynamic Weighted Ensemble (ACDWE) framework.

- The proposed framework integrates four supervised tree-based ensemble models (Random Forest, XGBoost, LightGBM, and Extra Trees) with dynamic confidence-weighted decision aggregation.

- A Hybrid Feature Selection (HFS) strategy eliminated over 60% of redundant attributes, enhancing classification accuracy while significantly lowering inference latency.
- Validation across three benchmark datasets (CICIoT2023, Bot-IoT, and UNSW-NB15) demonstrated superior overall performance (98.45% average accuracy, 98.10% Detection Rate, and 0.85% False Alarm Rate) compared to individual base classifiers and static voting systems.

6.2 Future Work

Future research directions include:

1. **Lightweight Edge Hardware Deployment:** Quantizing and compiling the ACDWE framework into ONNX/TensorRT format for low-power microcontrollers and Raspberry Pi-class IoT edge gateways.
2. **Zero-Day Threat Detection:** Integrating unsupervised autoencoders alongside ACDWE to identify completely novel attack signatures without pre-labeled training data.
3. **Federated Learning Integration:** Extending the architecture to support privacy-preserving collaborative model training across distributed IoT nodes.

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