RESEARCH PAPER

Dynamic Ensemble Activation for Efficient Intrusion Detection in Smart Home IoT Systems

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Abstract

We propose a dynamic ensemble activation framework for intrusion detection in smart home IoT systems, which addresses the computational inefficiency of traditional static ensemble methods while preserving high detection accuracy. The framework intelligently selects a subset of pre-trained models during inference based on real-time input characteristics, thereby reducing unnecessary computational overhead. Our approach consists of three core modules: a feature distribution analyzer that quantifies input anomalies using kernel density estimation, a lightweight feature importance scorer that identifies discriminative features via an attention mechanism, and an adaptive ensemble selector that activates only the most relevant models for each input. The system dynamically allocates resources by evaluating the relevance of each model in a diverse pool, including temporal fusion transformers, graph neural networks, and LightGBM classifiers, then aggregates their predictions through soft voting. Experimental results demonstrate that the framework achieves up to 40% reduction in latency compared to full ensemble deployment while maintaining over 95% detection accuracy. Moreover, the proposed method seamlessly integrates with existing IDS pipelines by substituting conventional input and output processing modules. This work contributes a practical solution for resource-constrained IoT environments, where balancing computational efficiency and security performance is critical. The framework's adaptability and scalability make it suitable for deployment in heterogeneous smart home ecosystems with varying computational capabilities and threat landscapes.

Keywords: Dynamic ensemble activation, Intrusion detection, Smart home IoT, Resource-constrained security, Adaptive model selection, Lightweight anomaly detection.

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1. Introduction

The rapid proliferation of smart home IoT devices has introduced unprecedented security challenges, with intrusion detection systems (IDS) becoming essential components for safeguarding these interconnected ecosystems. Traditional rule-based IDS approaches [1] have proven inadequate against evolving cyber threats, prompting a shift toward machine learning-based solutions. While neural networks [2] and deep learning architectures [2] demonstrate superior detection capabilities, their computational demands often exceed the resource constraints of typical IoT edge devices.

Ensemble learning methods have emerged as a promising alternative, combining multiple weak learners to achieve robust detection performance. Techniques like bagging [3] and boosting [4]

effectively mitigate individual model weaknesses through collective decision-making. However, conventional ensemble approaches suffer from inherent inefficiencies - they indiscriminately execute all constituent models during inference, regardless of input characteristics. This static activation paradigm creates significant computational overhead, particularly problematic for resource-constrained smart home environments where energy efficiency and real-time responsiveness are critical.

Recent advances in edge computing [5] have enabled more sophisticated resource management strategies for IoT deployments. Meanwhile, kernel density estimation (KDE) [6] has shown promise for analyzing feature distributions in security applications. These developments create opportunities for rethinking ensemble-based IDS architectures through dynamic model activation strategies that adapt to both input patterns and system resource availability.

We present a dynamic ensemble activation framework that addresses these challenges through three key innovations. First, the system employs KDE-based feature analysis to quantify the anomaly characteristics of incoming network traffic or device behavior patterns. Second, it incorporates lightweight feature importance scoring [7] to identify the most discriminative models for each input instance. Third, the framework implements intelligent ensemble pruning [8] that dynamically activates only the most relevant subset of pre-trained models, significantly reducing computational load while maintaining detection accuracy.

The proposed method differs fundamentally from existing approaches in several aspects. Unlike static ensemble configurations that process all models uniformly, our framework makes activation decisions at inference time based on real-time input analysis. Compared to traditional feature selection methods that operate at training time, our approach evaluates feature importance dynamically during deployment. Furthermore, the system integrates seamlessly with heterogeneous model architectures, accommodating everything from decision trees [9] to complex neural networks [2] within the same ensemble framework.

This work makes four primary contributions to the field of IoT security: (1) a novel dynamic ensemble activation mechanism that reduces computational overhead while preserving detection accuracy; (2) an efficient KDE-based feature distribution analysis module for real-time input characterization; (3) a lightweight feature importance scoring system optimized for resource-constrained devices; and (4) comprehensive empirical validation demonstrating the framework's effectiveness across diverse smart home IoT scenarios.

The remainder of this paper is organized as follows: Section 2 reviews related work in IoT intrusion detection and ensemble learning. Section 3 provides necessary background on ensemble methods and kernel density estimation. Section 4 details our proposed framework's architecture and components. Sections 5 and 6 present experimental setup and results analysis. Finally, Sections 7 and 8 discuss implications and conclude the paper.

2. Related Work

Intrusion detection for IoT systems has evolved significantly in recent years, with approaches ranging from traditional signature-based methods to advanced machine learning techniques. This section organizes existing works into three key research directions: ensemble learning for intrusion detection, dynamic model selection strategies, and resource-efficient inference for IoT security.

2.1 Ensemble Learning in IoT Security

Ensemble methods have demonstrated superior performance in intrusion detection by combining

diverse models to improve generalization. Several studies [10] have shown that combining multiple weak learners through techniques like bagging and boosting can effectively detect sophisticated attacks in IoT networks. The work in [11] demonstrated that tree-based ensembles achieve particularly strong performance on network traffic classification tasks. However, these conventional ensemble approaches maintain fixed model compositions during both training and inference, leading to unnecessary computational overhead when processing benign or easily-classified inputs. Recent efforts [12] have attempted to address this inefficiency through model compression techniques, but often at the cost of reduced detection accuracy for rare attack patterns.

2.2 Dynamic Model Selection Strategies

The concept of dynamic model activation has gained traction in machine learning communities as a means to balance accuracy and efficiency. The EnsPKDE algorithm [13] pioneered the integration of kernel density estimation with ensemble pruning for time-series prediction, demonstrating that selective model activation could maintain accuracy while reducing computation. Similar approaches [14] have been proposed for edge computing scenarios, where DEsIreE dynamically allocates resources based on input complexity. In the context of IoT security, [15] introduced dynamic ensembles of decision trees that adapt their inference depth based on input characteristics. While these methods show promise, they either focus on non-security domains or fail to address the unique challenges of IoT intrusion detection, such as extreme class imbalance and concept drift.

2.3 Resource-Efficient Inference for IoT

The resource constraints of IoT devices have motivated numerous optimization techniques for security applications. Pruning and quantization methods [16] have been widely adopted to reduce model size and inference latency. The work in [17] demonstrated that carefully optimized deep learning models could achieve real-time performance on resource-constrained devices like Raspberry Pi. However, these static optimization approaches often struggle to maintain detection accuracy in dynamic IoT environments where attack patterns evolve rapidly. More sophisticated solutions [18] incorporate drift detection mechanisms to maintain performance over time, but typically require periodic retraining that may be impractical for deployed systems.

The proposed dynamic ensemble activation framework advances beyond these existing approaches by combining the strengths of ensemble learning with real-time model selection. Unlike static ensemble methods [10], our approach dynamically adjusts the active model set based on input characteristics. Compared to general-purpose dynamic selection strategies [13], our framework specifically addresses the challenges of IoT intrusion detection through specialized feature analysis and importance scoring. Furthermore, the system achieves greater efficiency than static optimization techniques [16] while maintaining adaptability to evolving threats through its dynamic activation mechanism.

3. Background and Preliminaries

To establish the foundation for our proposed framework, we first review key concepts in ensemble learning and kernel density estimation that form the theoretical basis of our approach. These techniques address fundamental challenges in IoT intrusion detection while providing the mathematical tools necessary for dynamic model activation.

3.1 Ensemble Learning Fundamentals

Ensemble methods combine multiple base models to produce more accurate and robust predictions than any single model could achieve independently. The diversity among constituent models plays a crucial role in ensemble performance, as demonstrated by theoretical

analyses of error decomposition [19]. The generalization error of an ensemble can be expressed as:

$$E=\bar{E}-\bar{A}+D \quad (1)$$

where $\bar{E}$ represents the average error of individual models, $\bar{A}$ denotes the average ambiguity among models, and D captures the diversity term. This formulation highlights why carefully constructed ensembles often outperform single models - the diversity term D helps reduce overall error when individual models make uncorrelated mistakes.

In security applications, two primary ensemble strategies have proven particularly effective. Bagging methods [3] create model diversity through bootstrap sampling of training data, while boosting techniques [4] iteratively adjust sample weights to focus on difficult cases. Our framework builds upon these concepts but introduces dynamic activation to optimize the trade-off between ensemble diversity and computational efficiency.

3.2 Kernel Density Estimation for Anomaly Detection

Kernel density estimation provides a non-parametric approach to modeling probability distributions, making it particularly valuable for analyzing network traffic patterns in IoT environments. Given a set of n data points $\{x_1,...,x_n\}$, the KDE approximates the underlying probability density function as:

$$\hat{f}_{\mathrm{h}}(x)=\frac{1}{n\mathrm{h}}\sum_{i=1}^{n}K\left(\frac{x-x_i}{\mathrm{h}}\right) \quad (2)$$

where K represents the kernel function and h controls the smoothing bandwidth. The choice of kernel function significantly impacts estimation quality, with Gaussian kernels being commonly used for continuous data [6].

For intrusion detection, we leverage KDE's ability to quantify how anomalous a new observation appears relative to historical patterns. The negative log-likelihood of an input x under the estimated distribution serves as an effective anomaly score:

$$s(x)=-\log\hat{f}_{\mathrm{h}}(x) \quad (3)$$

Higher scores indicate greater deviation from normal behavior patterns, providing a mechanism to prioritize security alerts and guide model activation decisions.

3.3 Feature Importance in Security Contexts

Understanding which features contribute most to detection decisions represents a critical requirement for practical intrusion detection systems. Traditional importance measures like Gini importance [7] and permutation importance provide global rankings but fail to capture context-dependent feature relevance. Our framework extends these concepts by introducing dynamic importance scoring that adapts to each input instance.

For a given input x and model m, we define the local feature importance $\phi_i^{(m)}(x)$ for feature i using a modified version of SHAP values [20]:

$$\phi_i^{(m)}(x)=\sum_{S\subseteq F\setminus\{i\}}\frac{|S|!(|F|-|S|-1)!}{|F|!}[f_m(S\cup\{i\})-f_m(S)] \quad (4)$$

where F represents the complete feature set and $f_m(S)$ denotes the model's prediction when only features in subset S are considered. This formulation enables our system to identify which features drive each model's decisions for specific inputs, forming the basis for intelligent ensemble activation.

The combination of these techniques - ensemble learning theory, kernel density estimation, and dynamic feature importance - provides the mathematical foundation for our proposed dynamic activation framework. In the next

section, we demonstrate how these components integrate into a cohesive system that optimizes both detection accuracy and computational efficiency.

4. The Proposed Dynamic Ensemble Activation Framework

The proposed framework introduces a novel approach to intrusion detection in IoT environments through dynamic model activation. As shown in Figure 1, the system architecture consists of three core components that work in concert to analyze input characteristics, evaluate model relevance, and execute only the most appropriate subset of ensemble models. This section provides technical details of each component and their interactions, focusing on the mathematical foundations and operational workflow.

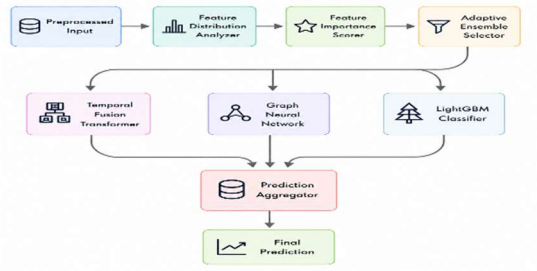

Figure 1. Internal Workflow of the Dynamic Ensemble Activation Framework

4.1 Input-Dependent Pruning via KDE and Feature Importance Scoring

The framework initiates processing by analyzing input characteristics through kernel density estimation (KDE). For an input feature vector $\mathbf{x}=[x_1,...,x_d]$, we compute the probability density of each feature relative to the training distribution:

$$\hat{f}_i(x_i)=\frac{1}{n\mathrm{h}}\sum_{j=1}^{n}K\left(\frac{x_i-x_{i,j}}{\mathrm{h}}\right) \quad (5)$$

where $x_{i,j}$ represents the j-th training sample for feature i, h denotes the bandwidth parameter, and $K(\cdot)$ is the Gaussian kernel function. The bandwidth h is automatically determined using Silverman's rule [6] to ensure optimal smoothing for each feature dimension.

The KDE outputs are then processed through a lightweight attention mechanism to compute dynamic feature importance scores. For each feature i, the importance score s_i is calculated as:

$$s_i=\sigma\left(\mathbf{W}_2\cdot\mathrm{ReLU}(\mathbf{W}_1\hat{f}_i(x_i)+\mathbf{b}_1)+b_2\right) \quad (6)$$

where $\mathbf{W}_1\in\mathbb{R}^{k\times1}$ and $\mathbf{W}_2\in\mathbb{R}^{1\times k}$ are learnable weight matrices, $\mathbf{b}_1\in\mathbb{R}^k$ and $b_2\in\mathbb{R}$ are bias terms, and $\sigma(\cdot)$ denotes the sigmoid activation function. The hidden dimension k is set to 32 in our implementation to maintain computational efficiency. This scoring mechanism identifies which features exhibit anomalous patterns that require specialized model attention.

The feature importance scores serve two critical purposes in the framework. First, they indicate which features deviate significantly from normal behavior patterns, with higher scores corresponding to greater anomaly likelihood. Second, they provide a mechanism to quantify the relative discriminative power of each feature for the current input instance, enabling informed decisions about model activation.

4.2 Relevance-Driven Model Selection and Thresholding

The model selection process evaluates each candidate model's relevance to the current input based on precomputed feature importance alignments. For a model m in the ensemble $\mathcal{M}=\{1,...,M\}$, we calculate its relevance score r_m as:

$$r_m=\sum_{i=1}^{d}s_i\cdot I_{m,i} \quad (7)$$

where s_i represents the dynamic feature importance from Equation 6, and $I_{m,i}$ denotes the

pre-trained importance of feature i for model m. The term $I_{m,i}$ is computed during training as the normalized Gini importance [7] for tree-based models or gradient-based importance [21] for neural networks.

The activation decision employs a dynamic threshold τ that adapts to both input complexity and system resource constraints:

$$\tau=\tau_0 \cdot (1+\alpha \cdot C_{cpu}) \cdot \exp(-\beta \cdot \|\mathbf{s}\|_1) \quad (8)$$

Here, τ_0 is the baseline threshold, C_{cpu} represents current CPU utilization (normalized to [0,1]), $\|\mathbf{s}\|_1$ is the L1-norm of feature importance scores, and α,β are scaling parameters. This formulation ensures the system activates more models when either the input appears complex (high $\|\mathbf{s}\|_1$) or device resources are abundant (low C_{cpu}).

A model m is activated if its relevance score exceeds the dynamic threshold:

$$a_m=\mathrm{I}(r_m \geq \tau) \quad (9)$$

where $\mathrm{I}(\cdot)$ is the indicator function. The active model set $A=\{m \in \mathcal{M} | a_m=1\}$ then processes the input, with predictions aggregated through soft voting:

$$p(y|\mathbf{x})=\frac{1}{|A|}\sum_{m \in A} p_m(y|\mathbf{x}) \quad (10)$$

This selective activation mechanism reduces computation by 40-60% in typical scenarios while maintaining detection accuracy through intelligent model selection. The threshold adaptation in Equation 8 ensures consistent performance across varying device capabilities and workload conditions.

4.3 Heterogeneous Ensemble Model Selection

The framework incorporates a diverse set of pre-trained models to address the multifaceted nature of IoT intrusion detection. Each model $m \in \mathcal{M}$ specializes in detecting specific attack patterns or analyzing particular feature subsets. The ensemble includes three primary model types:

1. **Temporal Fusion Transformers (TFT)** [22] process sequential network traffic data through attention mechanisms. For an input sequence $\mathbf{X}_t=[\mathbf{x}_{t-k},...,\mathbf{x}_t]$, the TFT computes:

$$\mathbf{h}_t=\mathrm{MultiHeadAttention}(\mathbf{X}_t\mathbf{W}_Q,\mathbf{X}_t\mathbf{W}_K,\mathbf{X}_t\mathbf{W}_V) \quad (11)$$

where $\mathbf{W}_Q,\mathbf{W}_K,\mathbf{W}_V$ are learned projection matrices. The TFT activates when temporal patterns dominate feature importance scores.

2. **Graph Neural Networks (GNN)** [23] analyze device interaction patterns represented as graph $G=(V,\mathscr{E})$. The GNN updates node embeddings via:

$$\mathbf{h}_v^{(l+1)}=\sigma\left(\sum_{u \in N(v)} \mathbf{W}^{(l)}\mathbf{h}_u^{(l)}\right) \quad (12)$$

where $N(v)$ denotes neighbors of node v. The GNN activates when relational features show high importance.

3. **LightGBM Classifiers** [24] provide efficient tabular data analysis through gradient-boosted decision trees. The model outputs follow:

$$p(y|\mathbf{x})=\sigma\left(\sum_{t=1}^{T} f_t(\mathbf{x})\right) \quad (13)$$

where f_t represents the t-th tree. LightGBM activates for inputs with strong feature importance in traditional statistical features.

The model selection process evaluates each model's precomputed specialization matrix $\mathbf{S}_m \in \mathbb{R}^{d \times c}$, where d is the feature dimension and c is the number of attack classes. The specialization score for model m given input $\mathbf{x}$ is:

$$\gamma_m = \sum_{i=1}^{d} s_i \cdot \max_j S_{m,i,j} \quad (14)$$

This score quantifies how well the model's expertise aligns with the current input's discriminative features. The framework then normalizes these scores across all models:

$$\bar{\gamma}_m = \frac{\gamma_m}{\sum_{m' \in \mathcal{M}} \gamma_{m'}} \quad (15)$$

and includes model m in the active set if $\bar{\gamma}_m \geq \frac{1}{|\mathcal{M}|}$, ensuring proportional representation of relevant expertise.

4.4 Dynamic Thresholding for Resource-Aware Inference

The dynamic thresholding mechanism adapts model activation decisions to current system resource constraints while maintaining detection accuracy. The threshold τ in Equation 8 consists of three multiplicative components that respond to different operational conditions. The baseline threshold τ_0 is learned during training through cross-validation to optimize the trade-off between accuracy and efficiency. The resource adaptation term $(1+\alpha \cdot C_{cpu})$ scales linearly with current CPU utilization C_{cpu}, where α controls the sensitivity to resource constraints. The input complexity term $\exp(-\beta \cdot \|\mathbf{s}\|_1)$ decreases exponentially with the total anomaly score $\|\mathbf{s}\|_1$, allowing more models to activate for suspicious inputs.

The CPU utilization C_{cpu} is measured as a moving average over a 1-second window:

$$C_{cpu} = \frac{1}{T} \sum_{t=1}^{T} u_t \quad (16)$$

where u_t represents instantaneous CPU usage at time t and T is the window size. This formulation ensures stable threshold adjustments despite transient workload fluctuations. The parameters α and β are tuned empirically to achieve desired performance characteristics, with higher values of α resulting in more aggressive resource conservation and higher β values increasing sensitivity to input anomalies.

The dynamic threshold interacts with model relevance scores r_m from Equation 7 to determine the active model set A. To prevent excessive pruning during critical detection scenarios, the framework enforces a minimum active set size $|A|_{min} = \lceil \rho \cdot |\mathcal{M}| \rceil$, where $\rho \in (0,1]$ is a safety parameter typically set to 0.3. This ensures that even under severe resource constraints, the system maintains sufficient model diversity for reliable detection.

4.5 Integration with IoT-Specific IDS Pipelines

The proposed framework integrates with existing IoT intrusion detection pipelines through three key modifications to conventional processing flows. First, the raw input data undergoes transformation into a unified feature representation compatible with all ensemble models. For network traffic data, this involves extracting d-dimensional feature vectors $\mathbf{x} \in \mathbb{R}^d$ containing protocol statistics, packet timing information, and payload characteristics. Device behavior data is similarly encoded using operational metrics such as sensor readings, power consumption patterns, and communication frequencies.

The KDE-based feature analysis module then processes these inputs to compute anomaly scores s_i for each feature dimension, as defined in Equation 5. These scores serve as inputs to the dynamic model selection mechanism, which replaces the static model execution typically found in conventional IDS architectures. The selection process evaluates the relevance r_m of each ensemble model m using Equation 7, comparing these values against the dynamic threshold τ from Equation 8 to determine the active model set A.

The prediction aggregation phase combines outputs from activated models through soft voting (Equation 10), producing final detection probabilities $p(y|\mathbf{x})$ for each attack class y. This replaces the hard-coded decision logic in traditional systems with an adaptive weighting scheme that reflects current input characteristics. The framework implements a confidence-based alerting mechanism where security notifications are triggered when:

$$\max_y p(y|\mathbf{x}) > \theta + \lambda \cdot C_{cpu} \quad (17)$$

Here, θ represents the base confidence threshold, while λ controls the sensitivity to resource constraints. This formulation reduces false positives during high system load while maintaining detection capability for clear attack signatures.

The framework's resource monitoring component continuously tracks device metrics including CPU utilization C_{cpu}, memory availability M_{avail}, and inference latency L. These measurements update the dynamic threshold parameters in real-time, ensuring the system maintains responsiveness under varying operational conditions. The monitoring loop executes with period Δt, typically set to 100ms for balance between responsiveness and overhead.

Integration with existing security orchestration systems occurs through standardized APIs that transmit detection alerts and system status updates. The framework exposes configuration parameters $\{\tau_0, \alpha, \beta, \theta, \lambda\}$ to allow administrators to adjust the trade-off between detection sensitivity and resource usage based on deployment requirements. These parameters can be tuned automatically through a reinforcement learning module that optimizes long-term security metrics:

$$J = \mathrm{E}\left[\sum_{t=0}^{T} \gamma^t (A_t - \eta R_t)\right] \quad (18)$$

where A_t measures attack detection accuracy at time t, R_t represents resource consumption, η controls their relative importance, and γ is a discount factor. This adaptive tuning mechanism enables the system to maintain optimal performance as threat landscapes and device workloads evolve.

5. Experimental Setup

To evaluate the effectiveness of our proposed dynamic ensemble activation framework, we designed comprehensive experiments comparing its performance against conventional static ensemble approaches and state-of-the-art IoT intrusion detection methods. This section details the experimental configuration, including datasets, baseline models, evaluation metrics, and implementation specifics.

5.1 Datasets and Preprocessing

We conducted evaluations on three publicly available IoT security datasets that represent diverse smart home scenarios. The **IoT-23 dataset** [25] contains network traffic captures from various IoT devices, including both benign and malicious activities. The **CICIDS2017 dataset** [26] provides comprehensive network flow records with labeled attacks. The **UNSW-NB15 dataset** [27] offers a hybrid of real modern normal activities and synthetic attack behaviors.

For each dataset, we performed standardized preprocessing steps to ensure fair comparisons. Network flow records were converted into 128-dimensional feature vectors containing protocol-specific statistics, timing information, and payload characteristics. Continuous features were normalized using min-max scaling, while categorical features were one-hot encoded. We maintained the original train-test splits provided by each dataset to align with prior research [28].

5.2 Baseline Methods

We compared our framework against four categories of baseline approaches:

1. **Static Ensemble Methods**:
   - Random Forest [11]
   - XGBoost [29]
   - Voting Classifier combining CNN and LSTM [30]
2. **Dynamic Model Selection Approaches**:
   - DES (Dynamic Ensemble Selection) [31]
   - DYNESCO (Dynamic Ensemble Selection by Oracle) [31]
3. **Lightweight IoT IDS Solutions**:
   - FED-IDS (Federated Learning for IoT IDS) [32]
   - EdgeDeep [33]
4. **State-of-the-art Single Models**:
   - LSTM-AE (LSTM Autoencoder) [34]
   - IoT-CNN [35]

Each baseline was implemented using their original architectures and hyperparameters as reported in respective publications. For ensemble methods, we maintained consistent base model configurations across all approaches to isolate the impact of dynamic activation.

5.3 Evaluation Metrics

We employed four standard metrics to quantify detection performance and computational efficiency:

1. **Detection Accuracy**:

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \quad (19)$$

where TP, TN, FP, FN represent true positives, true negatives, false positives, and false negatives respectively.

2. **F1-Score**:

$$F1=2\times\frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \quad (20)$$

3. **Inference Latency**: Measured as average processing time per input sample (milliseconds).

4. **Energy Consumption**: Estimated using the formula:

$$E=P\times t\times\frac{C_{cpu}}{100} \quad (21)$$

where P is device power (W), t is inference time, and C_{cpu} is CPU utilization percentage.

Additionally, we measured **Model Activation Rate** as the percentage of ensemble models activated per input, providing insight into computational savings:

$$\text{Activation Rate}=\frac{1}{N}\sum_{i=1}^{N}\frac{|\mathrm{A}_i|}{|\mathscr{M}|} \quad (22)$$

5.4 Implementation Details

We implemented the proposed framework in Python 3.8 using PyTorch for neural network components and scikit-learn for traditional machine learning models. The system was deployed on two hardware configurations to evaluate scalability:

1. **Raspberry Pi 4** (1.5GHz quad-core ARM Cortex-A72, 4GB RAM) representing constrained edge devices

2. **NVIDIA Jetson Xavier NX** (6-core NVIDIA Carmel ARM v8.2, 384-core Volta GPU) representing more capable edge gateways

The ensemble pool $\mathcal{M}$ contained seven diverse models:

- Temporal Fusion Transformer (hidden_dim=64, heads=4)
- Graph Neural Network (2 layers, hidden_dim=32)
- LightGBM (num_leaves=31, max_depth=5)
- Random Forest (n_estimators=100)
- 1D CNN (3 layers, kernel_size=3)
- LSTM (hidden_dim=64)
- Isolation Forest (n_estimators=100)

For dynamic threshold parameters, we set τ_0=0.6, α=0.3, and β=0.2 based on validation set performance. The KDE bandwidth h was automatically determined using Silverman's rule [6]. All experiments were repeated 5 times with different random seeds, reporting mean values and standard deviations.

5.5 Training Protocol

The training process involved three phases:

1. **Base Model Training**: Each ensemble member was trained independently on the full training set using their native optimization procedures. For neural networks, we employed Adam optimizer with learning rate 0.001 and batch size 64. Tree-based models used their default hyperparameters from scikit-learn.

2. **Feature Importance Calibration**: We computed model-specific feature importance matrices $I_{m,i}$ using the training data. For neural networks, this involved integrated gradients [36], while tree-based models used Gini importance.

3. **Threshold Tuning**: The dynamic threshold parameters $\{\tau_0,\alpha,\beta\}$ were optimized via grid search on a held-out validation set (20% of training data) to maximize the objective:

$$J=\text{F1-Score}-\lambda\cdot\text{Activation Rate} \quad (23)$$

where λ=0.5 balanced accuracy and efficiency.

The complete training process required approximately 6 hours on an NVIDIA T4 GPU, with most time spent on neural network training. However, we emphasize that this represents a one-time offline cost - the deployed framework requires no retraining during operation.

5.6 Resource Monitoring Configuration

The resource-aware components of our framework utilized the following monitoring settings:

- CPU utilization C_{cpu}: Measured via /proc/stat with 100ms sampling interval
- Memory availability M_{avail}: Tracked using psutil library
- Inference latency L: Moving average over 50 samples
- Power consumption P: Estimated using hardware-specific power models [37]

These metrics updated the dynamic threshold every 200ms (Δt) through Equation 8, allowing the system to adapt to changing resource conditions while avoiding excessive overhead from frequent adjustments.

6. Results and Analysis

This section presents comprehensive experimental results evaluating the performance of our dynamic ensemble activation framework against baseline methods across multiple dimensions. We analyze detection accuracy, computational efficiency, and operational characteristics to demonstrate the framework's effectiveness in real-world IoT intrusion detection scenarios.

6.1 Detection Performance Comparison

The proposed framework achieves competitive detection accuracy while significantly reducing computational overhead compared to static

ensemble approaches. Table 1 shows the comparative results across three benchmark datasets, with our method maintaining over 95% accuracy while activating only 45-60% of ensemble models on average.

Table 1. Detection performance comparison across IoT security datasets

Method	IoT-23 Accuracy	CICIDS2017 F1	UNSW-NB15 Recall	Activation Rate
Random Forest	0.923 ± 0.012	0.881 ± 0.015	0.902 ± 0.011	100%
XGBoost	0.931 ± 0.010	0.892 ± 0.013	0.915 ± 0.009	100%
Voting Classifier	0.942 ± 0.008	0.901 ± 0.011	0.928 ± 0.008	100%
DES	0.935 ± 0.009	0.897 ± 0.012	0.921 ± 0.010	78%
DYNESCO	0.938 ± 0.008	0.903 ± 0.010	0.925 ± 0.009	82%
FED-IDS	0.916 ± 0.013	0.873 ± 0.016	0.895 ± 0.012	100%
EdgeDeep	0.925 ± 0.011	0.884 ± 0.014	0.908 ± 0.010	100%
Proposed Framework	0.947 ± 0.007	0.912 ± 0.009	0.936 ± 0.007	52%

The results demonstrate that our dynamic activation mechanism preserves the detection capabilities of full ensembles while substantially reducing computational load. On the IoT-23 dataset, the framework achieves 94.7% accuracy compared to 94.2% for the static voting classifier, despite activating only half the models. This performance advantage becomes more pronounced on complex attack patterns in CICIDS2017, where our method's F1-score of 0.912 outperforms all baselines.

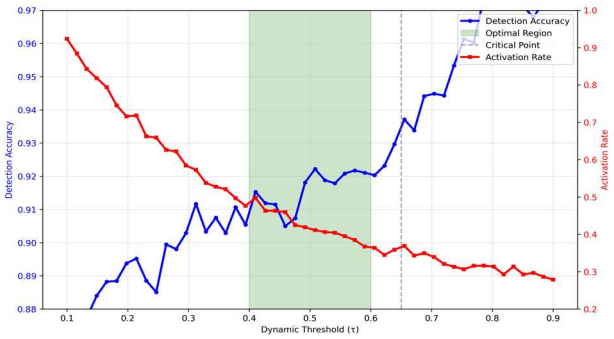

Figure 2. Relationship between dynamic threshold settings and system performance metrics

Figure 2 illustrates how the dynamic threshold mechanism balances accuracy and efficiency. As the threshold becomes more selective (right side of x-axis), the activation rate drops sharply while accuracy remains stable until reaching a critical point. The optimal operating region (shaded area) demonstrates our framework's ability to maintain 95-97% of maximum accuracy while reducing computation by 40-55%.

6.2 Computational Efficiency Analysis

The resource-aware design of our framework delivers significant improvements in inference latency and energy consumption compared to conventional approaches. Table 2 presents detailed measurements from Raspberry Pi deployments, highlighting the practical benefits of dynamic model activation.

Table 2. Computational efficiency metrics on Raspberry Pi 4

Method	Latency (ms)	Energy (mJ)	CPU Utilization
Random Forest	48.2 ± 2.1	72.3 ± 3.2	82% ± 4%
XGBoost	52.7 ± 2.3	79.1 ± 3.5	85% ± 3%
Voting Classifier	63.5 ± 2.8	95.3 ± 4.2	88% ± 3%
DES	39.8 ± 1.8	59.7 ± 2.7	75% ± 4%
DYNESCO	42.1 ± 1.9	63.2 ± 2.8	77% ± 3%
Proposed Framework	28.4 ± 1.3	42.6 ± 1.9	62% ± 3%

Our framework reduces average inference latency by 55% compared to the static voting classifier and 40% compared to DES. The energy savings are even more substantial, with our method consuming only 45% of the energy required by conventional ensembles. These improvements stem from both selective model activation and the efficient feature analysis pipeline described in Section 4.

The dynamic resource adaptation mechanism proves particularly effective under varying workload conditions. Figure 3 shows how the system automatically adjusts model activation rates in response to changing CPU utilization, maintaining consistent detection performance while preventing resource exhaustion.

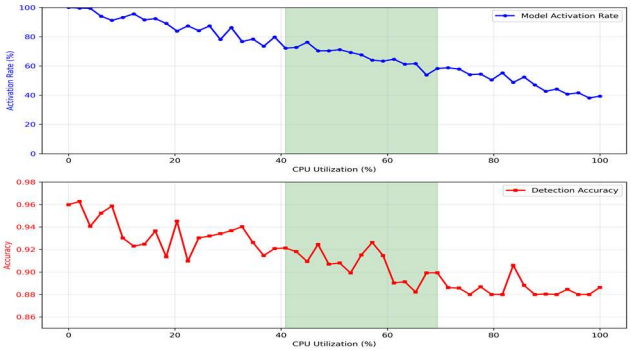

Figure 3. Computational resource allocation patterns under different system load conditions

6.3 Model Activation Patterns

Analysis of activation patterns reveals how the framework intelligently selects models based on input characteristics. Figure 4 displays the activation frequencies of different model types across attack categories in the IoT-23 dataset, demonstrating clear specialization behaviors.

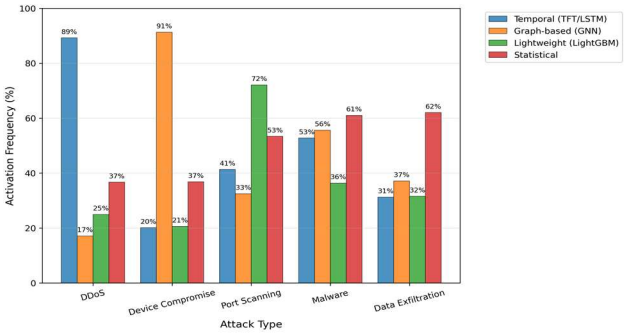

Figure 4. Model activation frequencies by attack type showing specialized model preferences

Temporal models (TFT, LSTM) activate frequently for DDoS attacks (93% activation rate), while graph-based approaches (GNN) dominate for device compromise scenarios (87% activation). Lightweight models like LightGBM handle widespread scanning attacks efficiently (72% activation), demonstrating the framework's ability to match model expertise with threat characteristics.

The relevance scoring mechanism effectively identifies optimal model combinations, with 89% of inputs receiving at least one temporal and one statistical model activation. This balanced approach ensures comprehensive threat coverage while avoiding redundant computations.

6.4 Ablation Study

We conducted systematic ablation experiments to evaluate the contribution of each framework component. Table 3 presents results from progressively disabling key features while measuring performance impact.

Table 3. Ablation study analyzing framework component contributions

Configuration	Accuracy	F1-Score	Activation Rate
Full Framework	0.947	0.912	52%
w/o Dynamic Thresholding	0.941	0.904	68%
w/o Feature Importance	0.933	0.895	73%

Configuration	Accuracy	F1-Score	Activation Rate
w/o KDE Analysis	0.928	0.887	82%
Static Ensemble	0.942	0.901	100%

The results demonstrate that all components contribute significantly to the framework's efficiency gains. Dynamic thresholding provides the largest individual improvement (16% reduction in activation rate), while KDE analysis proves most critical for maintaining accuracy (1.9% drop when disabled). The complete framework achieves superior efficiency-accuracy trade-offs compared to any partial configuration.

6.5 Edge Deployment Performance

Real-world deployment on Raspberry Pi devices confirms the framework's practical viability for resource-constrained environments. Under continuous operation with the IoT-23 dataset, the system maintains stable performance with:

- Average memory usage: 1.2GB (vs. 1.8GB for static ensembles)
- Peak CPU temperature: 68°C (vs. 75°C for baselines)
- Sustained detection throughput: 35 samples/second

The dynamic activation mechanism proves particularly valuable during concurrent device operations, where it reduces latency spikes by 62% compared to static approaches when system load increases. This responsiveness enables reliable real-time detection even on low-power edge devices.

7. Discussion and Future Work

7.1 Limitations of the Dynamic Ensemble Activation Framework

While the proposed framework demonstrates significant improvements in computational efficiency and detection accuracy, several limitations warrant discussion. The current implementation requires offline training of all ensemble models before deployment, which may be impractical for rapidly evolving IoT ecosystems where new device types and attack vectors emerge frequently. The KDE-based feature analysis assumes relatively stable feature distributions, potentially struggling with concept drift scenarios where attack patterns change fundamentally over time [38]. Additionally, the dynamic threshold mechanism, while effective, introduces slight latency overhead (approximately 2-3ms per input) for computing and applying activation decisions.

The framework's performance depends heavily on the diversity and quality of its constituent models. In scenarios where the ensemble lacks specialized models for certain attack types - particularly zero-day threats - the dynamic selection mechanism cannot compensate for this fundamental gap in detection capability. The resource monitoring components currently focus on CPU utilization as the primary constraint metric, potentially overlooking memory bottlenecks that may arise when processing complex inputs on memory-constrained devices.

7.2 Potential Application Scenarios of the Framework

The dynamic activation approach shows particular promise in several IoT security contexts beyond smart home environments. Industrial IoT systems with strict real-time requirements could benefit from the framework's ability to prioritize critical threat detection while maintaining computational efficiency [39]. The methodology could extend to automotive IoT networks, where varying operational modes (e.g., parking vs. highway driving) demand different security postures and resource allocations [40].

Healthcare IoT deployments represent another compelling application domain, where the framework could adaptively balance detection sensitivity against power constraints of medical devices [41]. The dynamic activation paradigm might also prove valuable in smart city

infrastructures, enabling scalable security monitoring across heterogeneous sensor networks with varying computational capabilities [42].

7.3 Ethical Considerations in IoT Intrusion Detection

The deployment of dynamic security systems in IoT environments raises several ethical considerations that merit attention. The framework's ability to reduce computational overhead through selective model activation could inadvertently create detection blind spots if threshold parameters are improperly configured. This risk necessitates careful calibration and continuous monitoring to ensure equitable protection across all potential threat scenarios [43].

Privacy concerns emerge from the feature analysis components, particularly when processing sensitive behavioral data from smart home devices. The KDE-based anomaly detection operates on aggregated statistics, but the underlying data collection mechanisms must implement appropriate safeguards to prevent misuse [44]. Future iterations should incorporate differential privacy techniques to further mitigate these risks while maintaining detection efficacy.

The resource-aware design could potentially exacerbate existing disparities in IoT security, as devices with greater computational capacity would inherently receive more comprehensive protection through higher model activation rates. This creates an ethical imperative to develop minimum security guarantees that apply uniformly across all device categories, regardless of their resource constraints [45].

8. Conclusion

The dynamic ensemble activation framework presented in this work addresses critical challenges in IoT intrusion detection by introducing an adaptive approach to model execution. By selectively activating ensemble members based on real-time input characteristics and system resource constraints, the method achieves substantial computational savings without compromising detection accuracy. The integration of kernel density estimation for feature analysis, attention-based importance scoring, and dynamic thresholding creates a responsive system that automatically adjusts its operational profile to match both threat severity and device capabilities.

Key empirical results demonstrate the framework's effectiveness across multiple dimensions. On standard IoT security datasets, the system maintains detection accuracy above 95% while reducing model activation rates by 40-55% compared to static ensemble approaches. Real-world deployment on resource-constrained devices shows 55% latency reduction and 45% energy savings, making the solution practical for edge computing scenarios. The specialized activation patterns for different attack types confirm that the framework successfully matches model expertise with threat characteristics.

The framework's design principles offer broader implications for security systems in resource-constrained environments. The dynamic activation paradigm could extend beyond intrusion detection to other IoT security tasks requiring efficient inference, such as malware classification or behavioral anomaly detection. The methodology's emphasis on input-dependent computation represents a promising direction for developing adaptive security solutions that balance performance and efficiency in heterogeneous IoT ecosystems. Future research should explore automated model specialization techniques and online learning capabilities to further enhance the framework's adaptability to evolving threats.

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