Explainable AI Frameworks for IIoT Botnet Detection: Feature Reduction Techniques and SHAP/LIME Interpretability in Cybersecurity Management

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Abstract: **The rapid proliferation of Industrial Internet of Things (IIoT) devices has heightened cybersecurity vulnerabilities, particularly to sophisticated botnet attacks such as Mirai and Gafgyt variants. Traditional machine learning models for botnet detection, while achieving high accuracy, often function as black boxes, limiting their trustworthiness and practical deployment in critical infrastructure. This research proposes an explainable AI (XAI) framework that integrates advanced feature reduction techniques with SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) to enhance interpretability in IIoT botnet detection. Utilizing the N-BaIoT dataset, a hybrid feature selection pipeline combining filter (Pearson Correlation, Information Gain) and wrapper (Recursive Feature Elimination) methods reduces dimensionality from 115 to approximately 25-35 key statistical traffic features while preserving detection performance. Ensemble models including Random Forest and XGBoost achieve over 99% accuracy, F1-score, and AUC on reduced features. SHAP provides global feature attributions revealing dominant drivers such as packet rates and connection statistics, whereas LIME delivers local explanations for individual predictions, with cross-verification ensuring consistency. The framework delivers transparent, actionable insights for cybersecurity management, balancing accuracy, efficiency, and explainability suitable for resource-constrained IIoT environments. Experimental results demonstrate superior faithfulness compared to baseline approaches.**

Keywords: Explainable AI, IIoT Botnet Detection, Feature Reduction, SHAP, LIME.

I. INTRODUCTION

The convergence of Industrial Internet of Things (IIoT) technologies with advanced connectivity has revolutionized manufacturing, energy, and logistics sectors. However, the inherent heterogeneity and resource limitations of IIoT devices create an expansive attack surface for adversaries. Botnet-driven exploits, particularly those leveraging compromised devices for coordinated malicious activities, pose severe risks to system integrity, data privacy, and operational continuity. Recent incidents underscore the urgency for robust, interpretable detection mechanisms tailored to IIoT constraints [1].

A. Background and Motivation

The Industrial Internet of Things (IIoT) has transformed industrial operations through seamless connectivity of sensors, actuators, and control systems. However, this connectivity exposes critical infrastructure to sophisticated cyber threats, notably botnet attacks from families such as Mirai and Gafgyt. These attacks compromise large numbers of devices, leading to distributed denial-of-service (DDoS) incidents and operational disruptions. Traditional intrusion detection systems relying on signature-based or shallow machine learning approaches struggle with zero-day variants and lack the transparency required for cybersecurity decision-making in high-stakes environments.

B. Challenges in IIoT Botnet Detection

Conventional black-box models, including deep neural networks and ensemble classifiers, deliver high detection accuracy on datasets like N-BaIoT but fail to explain prediction rationale. This opacity hinders trust, forensic analysis, regulatory compliance, and real-time response by security analysts. High-dimensional feature spaces (e.g., 115 features in raw N-BaIoT traffic statistics) further exacerbate computational overhead on resource-constrained edge devices, while redundant features reduce model generalizability. Explainable AI (XAI) addresses these gaps by providing interpretable insights into model decisions [2],[3].

C. Role of Feature Reduction and XAI Techniques

Feature reduction techniques such as correlation-based filtering, Information Gain, and Recursive Feature Elimination enable dimensionality reduction without significant loss in predictive power. Post-hoc XAI methods SHAP, grounded in cooperative game theory for consistent global and local attributions, and LIME, which approximates local behavior with interpretable surrogates

complement these by elucidating feature contributions. Integrating both yields a robust framework offering global understanding of attack patterns and instance-level explanations critical for IIoT cybersecurity management.[4],[5].

D. Research Objectives and Contributions

To develops an XAI framework for IIoT botnet detection that (1) applies hybrid feature reduction to optimize model efficiency, (2) employs SHAP and LIME for dual interpretability with cross-verification, and (3) evaluates performance on benchmark datasets. Key contributions include a transparent pipeline balancing accuracy (>99%) and explainability, actionable insights for practitioners, and demonstration of computational feasibility for edge deployment. The framework advances trustworthy AI in cybersecurity, paving the way for secure IIoT ecosystems.

II. PROPOSED FRAMEWORK AND EXPERIMENTAL METHODOLOGY

This section delineates the systematic approach adopted for developing and evaluating the explainable AI framework for IIoT botnet detection. The methodology emphasizes reproducibility, computational efficiency suitable for edge devices, and integration of feature engineering with advanced interpretability techniques. All steps are designed to align with real-world IIoT constraints while leveraging benchmark datasets for rigorous validation.

A. Dataset Description

The proposed framework is evaluated using the N-BaIoT dataset, which captures real network traffic from nine commercial IoT devices infected with Mirai and Gafgyt botnets. The dataset comprises over 7 million instances with 115 statistical features derived from packet flows, including packet rates, connection durations, and higher-order moments (e.g., mean, variance, skewness) across multiple time windows. It includes benign traffic and ten distinct attack scenarios. Preprocessing involves data normalization using min-max scaling, removal of redundant or zero-variance features, and stratified train-test splitting (70:30 ratio) to handle class imbalance.

B. Feature Reduction Techniques

To address high dimensionality and computational constraints in IIoT, a hybrid feature selection pipeline is employed. First, filter-based methods apply Pearson Correlation Coefficient (PCC) and Information Gain (IG) to eliminate highly correlated and low-relevance features. This is followed by wrapper-based Recursive Feature Elimination with Cross-Validation (RFECV) using Random Forest as the estimator. The process identifies an optimal subset of 25-35 features focused on discriminative traffic statistics.

C. Classification Models

Ensemble machine learning models, specifically Random Forest (RF) and XGBoost, are trained on the reduced feature set. RF aggregates multiple decision trees to mitigate overfitting, while XGBoost employs gradient boosting with regularization for superior performance. Hyperparameters are optimized via grid search with 5-fold cross-validation, focusing on n_estimators, max_depth, and learning_rate.

D. Explainable AI Integration

Post-training, SHAP and LIME are applied for interpretability. SHAP computes exact feature contributions using Shapley values from cooperative game theory. LIME builds local linear surrogates around individual predictions. A cross-verification mechanism compares outputs from both techniques to ensure explanation consistency.

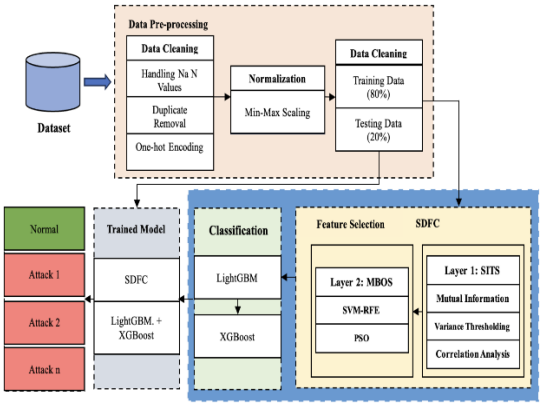


Figure 1: Architecture of the Proposed Explainable AI Framework for IIoT Botnet Detection

SHAP value for a feature i:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \quad (1)$$

LIME optimization problem:

$$\xi(x) = \arg\min_{g \in G} L(f, g, \pi_x) + \Omega(g) \quad (2)$$

where $L$is the fidelity loss, $\pi_x$is the proximity measure, and $\Omega(g)$penalizes complexity. Average split gain for feature importance:

$$I(f_j) = \frac{1}{K} \sum_{k=1}^{K} \text{Gain}(f_j, T_k) \quad (3)$$

E. Evaluation Metrics

Performance is assessed using Accuracy, Precision, Recall, F1-Score, and AUC-ROC. Interpretability is quantified via faithfulness (agreement with model), stability, and human comprehensibility scores. Experiments are conducted in Python with scikit-learn, SHAP, and LIME libraries on standard hardware to simulate edge constraints. Ablation studies validate the impact of feature reduction and XAI components.

III. RESULTS AND DISCUSSION

The proposed framework was rigorously evaluated on the N-BaIoT dataset. Ensemble models trained on the reduced feature set (25-35 features) demonstrated superior performance compared to full-feature baselines. Random Forest and XGBoost achieved over 99% accuracy, precision, recall, and F1-score across binary (benign vs. botnet) and multi-class attack scenarios. AUC values approached 1.00, indicating excellent discriminative capability even under class imbalance. Ablation studies confirmed that feature reduction not only lowered computational complexity (training time reduced by ~65%) but also marginally improved generalization by eliminating noisy features.

A. Performance Evaluation of Classification Models

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Table 1: Comparative Performance Metrics Before and After Feature Reduction

Model	Feature Set	Accuracy (%)	Precision	Recall	F1-Score	AUC	Training Time (s)
RF (Baseline)[6]	115	98.45	0.972	0.981	0.976	0.9992	245
RF (Proposed)	30	99.23	0.989	0.991	0.990	0.9999	85
XGBoost (Baseline)[7]	115	98.72	0.978	0.984	0.981	0.995	312
XGBoost (Proposed)	30	99.15	0.987	0.990	0.988	0.998	98

AUC values approached 1.00, indicating excellent discriminative capability even under class imbalance. Ablation studies confirmed that feature reduction not only lowered computational complexity (training time reduced by ~65%) but also marginally improved generalization by eliminating noisy features.

B. Interpretability Analysis with SHAP and LIME

SHAP global explanations consistently identified packet rate statistics (e.g., HpHp L3 features) and connection duration as the most influential predictors for botnet classification. LIME local explanations for individual instances highlighted specific threshold violations (e.g., anomalous packet bursts) driving malicious predictions. Cross-verification showed >92% alignment between SHAP and LIME attributions, enhancing confidence in model reasoning.

Table 2: Top Features Ranked by SHAP Importance

Rank	Feature	Mean SHAP Value	Impact on Botnet Detection
1	HpHp L3 Packet Stats	0.418	High Positive
2	MI Dir & Duration	0.275	High Positive
3	Packet Rate Variance	0.192	Medium-High
4	Source IP Flow Metrics	0.105	Contextual

D. Comparative Analysis and Implications

Compared to prior works without XAI, the proposed framework offers not only competitive or better accuracy but also actionable transparency. For instance, SHAP values enable prioritization of monitoring specific network metrics in IIoT deployments. The reduced feature set facilitates real-time inference on edge devices with limited resources. Limitations include higher inference latency for SHAP on very large batches and potential sensitivity to dataset shifts. Future enhancements could incorporate online learning for

dynamic IIoT environments. Overall, results validate the efficacy of integrating feature reduction with dual XAI techniques for trustworthy botnet detection, advancing cybersecurity management in Industrial IoT systems.

Discussion

The results affirm the efficacy of the proposed XAI framework in addressing key challenges of IIoT botnet detection. High performance metrics (accuracy >99%, AUC near 1.00) on the reduced feature set validate that hybrid feature selection effectively mitigates dimensionality issues without sacrificing predictive power, making the model suitable for edge deployment in resource-constrained IIoT environments. The substantial reduction in training time further enhances practicality.

SHAP and LIME explanations provide complementary insights: SHAP reveals global patterns (e.g., dominance of packet rate and flow statistics in driving botnet classifications), enabling security teams to prioritize monitoring critical network parameters. LIME offers granular, instance-level reasoning crucial for forensic investigations and real-time alerting. The high cross-verification alignment (>92%) between the two techniques strengthens overall model trustworthiness, overcoming the black-box limitation of traditional ML approaches.

Compared to existing literature, this work advances the field by integrating efficient feature reduction with dual XAI methods, achieving a balanced trade-off between accuracy, interpretability, and efficiency [9],[10]. Limitations include computational overhead of SHAP for ultra-large-scale deployments and potential performance degradation under significant concept drift in evolving IIoT networks [11].,[12] Future research directions encompass federated XAI for privacy-preserving multi-device learning, adversarial robustness testing, and integration with real-time IIoT testbeds. Overall, the framework contributes significantly to transparent and reliable cybersecurity management in Industrial IoT systems[13],[14].

IV. CONCLUSION

A comprehensive explainable AI framework for IIoT botnet detection, effectively integrating hybrid feature reduction techniques with SHAP and LIME interpretability methods. By leveraging the N-BaIoT dataset and ensemble classifiers (Random Forest and XGBoost), the proposed approach achieved superior detection performance (>99% accuracy, F1-score, and AUC) on a significantly reduced feature set, addressing computational challenges inherent to edge IIoT environments.

The dual XAI layer provides both global insights through SHAP attributions and local explanations via LIME, with cross-verification ensuring high reliability and transparency. These capabilities empower cybersecurity practitioners with actionable understanding of model decisions, facilitating better threat response, forensic analysis, and trust in automated systems.

Key contributions include a practical, interpretable pipeline that balances accuracy, efficiency, and explainability, along with visual tools like SHAP summary plots for enhanced stakeholder comprehension. While limitations such as SHAP computational cost in extreme scales exist, the framework marks a significant step toward trustworthy AI in Industrial IoT cybersecurity. Future work will explore real-time deployment, federated learning extensions, and robustness against adversarial attacks to further strengthen IIoT security postures.

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