International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 03 , March - 2026

Explainable AI-Based Lightweight Intrusion Detection System for Secure IoT Communication Protocols

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Abstract - The rapid proliferation of Internet of Things (IoT) devices has introduced significant security vulnerabilities, particularly within communication protocols such as MQTT and CoAP. Traditional Intrusion Detection Systems (IDS) often struggle with the resource constraints of IoT hardware or lack transparency in their decision-making processes. This paper proposes a lightweight, XAI-based IDS designed for edge deployment. By employing a pruned Random Forest model combined with SHAP (SHapley Additive exPlanations), our system achieves high detection accuracy while providing human-interpretable insights into identified threats. Experimental results on the IoT-23 dataset demonstrate that our model maintains a 98.4% F1-score with a 40% reduction in computational overhead compared to standard deep learning approaches.

Index Terms - Internet of Things (IoT), Explainable AI (XAI), Intrusion Detection System (IDS), MQTT, CoAP, SHAP, Lightweight Machine Learning.

I INTRODUCTION

The Internet of Things (IoT) ecosystem has expanded into critical sectors including healthcare, industrial automation, and smart cities. However, the heterogeneous nature of IoT communication protocols—primarily **MQTT** (Message Queuing Telemetry Transport) and **CoAP** (Constrained Application Protocol)—presents a vast attack surface for malicious actors.

Recent advancements in Artificial Intelligence (AI) have significantly improved IDS performance. Yet, two primary hurdles remain:

1. **Resource Constraints:** Deep learning models are often too "heavy" for battery-operated IoT sensors.
2. **The "Black Box" Problem:** High-performing models lack transparency, making it difficult for security analysts to trust or verify automated alerts.

This paper addresses these gaps by proposing a **Lightweight-XAI-IDS** framework.

II. RELATED WORK

Recent research has shifted toward **Edge AI** to reduce latency. Studies in 2025 highlighted the use of Tree-based models for their inherent efficiency on microcontrollers. Furthermore, the integration of **LIME** and **SHAP** has been explored to provide post-hoc explanations, though most current implementations remain too computationally expensive for real-time IoT monitoring. Our work differs by optimizing the feature selection process specifically for protocol-level anomalies.

III. PROPOSED METHODOLOGY

A. Data Preprocessing and Feature Engineering

We utilize the **IoT-23 dataset**, focusing on features specific to MQTT and CoAP headers (e.g., Keep-Alive timer, Payload length, and Topic levels). Data is normalized using Min-Max scaling to ensure uniformity across different protocol metrics.

B. Lightweight Model Architecture

To ensure low power consumption, we implement a **Pruned Random Forest (PRF)**. Unlike standard forests, the PRF limits tree depth and uses Gini importance to select only the top 10 most discriminative features.

$$Gini\ (D) = 1 - \sum_{i=1}^{n} Pi^{2}$$

Where Pi is the probability of an item with label i being chosen for a dataset D.

C. Explainability Module (SHAP)

We integrate **TreeSHAP**, a variant of SHAP optimized for tree-based models. It attributes an "importance value" to each feature for every specific alert. This allows the system to not only flag a "DDoS Attack" but also explain: *"Alert triggered*

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due to abnormal Request-to-Response ratio in CoAP packets."

IV. CASE STUDY: MITIGATING MIRAI-STYLE BOTNETS IN SMART MANUFACTURING

A. Scenario Setup

In a controlled Industrial IoT (IIoT) environment, 50 **ESP32-based sensors** (monitoring temperature and vibration) and 10 **actuators** were deployed. The communication was orchestrated via an **MQTT Broker** (Mosquitto) and a **CoAP Gateway**.

The "Attack Phase" involved injecting a **Mirai Botnet variant**, characterized by:

- **TCP SYN Flooding:** Exhausting the connection limits of the gateway.
- **MQTT Brute Force:** Attempting to guess credentials to gain "Publish" rights.
- **Packet Fragmentation:** Exploiting CoAP's UDP-based nature to bypass simple firewalls.
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B. Detection Performance

The Lightweight-XAI model was deployed on a **Raspberry Pi 4** acting as an Edge Gateway. The model monitored traffic features such as *Packet Inter-Arrival Time (IAT)*, *Flow Duration*, and *Payload Entropy*.

- **Detection Latency:** The system identified the attack within **140ms** of the first malicious burst.
- **Resource Usage:** CPU utilization remained below **12%**, and memory footprint was stabilized at **45MB**, significantly lower than a standard LSTM-based IDS which peaked at 85% CPU.

C. XAI-Driven Root Cause Analysis

During the MQTT Brute Force attempt, the system generated a **SHAP Force Plot**.

Interpretation: The model flagged the activity as "High Risk" (0.98 probability). The XAI module highlighted that the **"Connect Flags"** and **"Keep Alive"** intervals were the primary contributors to the alert.

Specifically, the "Connect Flags" showed repeated failed handshakes with incrementing "ClientIDs," a classic signature of a dictionary attack. Without the XAI component, a security admin might have misidentified the spike as a simple network congestion issue. With the explanation, the admin could immediately implement a **MAC-address lockout** and update the **Keep Alive** policy.

D. Lessons Learned

The case study confirmed that:

1. **Protocol-Specific Features** are more valuable than generic network headers for IoT security.
2. **Explainability reduces Mean Time to Respond (MTTR)** by providing actionable context to IT staff.
3. **Model Pruning** is essential to prevent "Edge Choke," where the security system itself consumes the resources intended for industrial applications.

V. RESULTS AND DISCUSSION

A. Performance Metrics

The system was evaluated against standard Deep Neural Networks (DNN) and Support Vector Machines (SVM).

Table I

Model	Accuracy	F1-Score	Inference Time (ms)
Standard DNN	99.10%	98.80%	12.4
SVM	94.20%	93.50%	4.2
Proposed PRF-XAI	**98.70%**	**98.40%**	**1.8**

B. Interpretability Analysis

By using SHAP summary plots, we identified that for **MQTT-based Man-in-the-Middle (MitM)** attacks, the "Duplicate Flag" and "Message ID" consistency were the most contributing factors.

C. Comparative Analysis of XAI Methods: SHAP vs. LIME

While both methods provide local explanations for model predictions, they differ significantly in computational complexity and consistency. The following table summarizes their performance during the Smart Factory case study:

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Table II: Comparison of XAI Frameworks for Edge-Deployed IDS

Metric	LIME (Local Interpretable Model-agnostic Explanations)	SHAP (SHapley Additive exPlanations)
Mathematical Foundation	Local Surrogate Models (Linear)	Game Theory (Shapley Values)
Explanation Consistency	Lower (Local perturbations can vary)	**Higher** (Mathematically proven consistency)
Feature Attribution	Approximate	**Exact** (for the specific model)
Computational Overhead	High (due to sampling/perturbations)	**Low** (via TreeSHAP optimization)
Inference Latency (ms)	~45 ms per explanation	**~12 ms per explanation**
Memory Footprint	Moderate	**Low** (Integrated into the Forest structure)

D. Discussion on XAI Efficiency

In our IoT communication scenario, **LIME** exhibited "instability" when explaining CoAP fragmentation attacks. Because LIME creates synthetic data points to test the model's boundaries, it occasionally generated feature combinations that were logically impossible in the CoAP protocol, leading to misleading explanations.

In contrast, **SHAP (specifically TreeSHAP)** leveraged the internal structure of our Pruned Random Forest. This allowed it to:

1. **Reduce Latency:** Since TreeSHAP does not require thousands of samples like LIME, it provided explanations nearly **3.7x faster**.
2. **Ensure Trust:** The Shapley values ensured that the "contribution" of each feature (e.g., *MQTT Topic Length*) summed up exactly to the difference between the actual prediction and the average prediction.

Key Finding: For real-time IoT security, the consistency and speed of TreeSHAP make it the superior choice over LIME, which is better suited for offline, model-agnostic post-mortem analysis.

E. Scalability Results

We also tested the system's ability to handle increasing numbers of IoT devices. The "Lightweight" nature of the model allowed the CPU load to scale linearly rather than exponentially.

- **10 Devices:** 4% CPU load.
- **50 Devices:** 12% CPU load.
- **100 Devices:** 21% CPU load (with explainability enabled).

This confirms the feasibility of deploying XAI-based IDS directly on edge gateways rather than relying on expensive cloud-based computation.

VI. FUTURE DIRECTIONS: TOWARD 6G-IOT SECURITY

The transition to **6G networks** introduces a paradigm shift from "connected things" to "connected intelligence." To maintain the security of secure IoT communication protocols in the 6G era, several research frontiers must be explored:

A. AI-Native Security and "Near-Zero" Latency

6G aims for sub-millisecond latency, which renders traditional cloud-based IDS obsolete. Future research should focus on **In-Network Intelligence**, where lightweight XAI models are embedded directly into the 6G Radio Access Network (RAN). This requires optimizing SHAP-based feature attribution to operate in microseconds without exhausting the limited energy budget of 6G micro-nodes.

B. Federated XAI for Privacy-Preserving Protocols

As 6G emphasizes user privacy, **Federated Learning (FL)** will be the standard for training IDS models across distributed IoT clusters. However, explaining a "Global Model" to "Local Nodes" remains a challenge. Future directions include developing **Federated XAI (Fed-XAI)** frameworks that can provide consistent explanations across heterogeneous devices (e.g., a smart wearable vs. an industrial robotic arm) without sharing raw protocol data.

C. Semantic Communication Security

6G will likely utilize **Semantic Communications**, where only the "meaning" of data is transmitted to save bandwidth. This introduces a new attack vector: *Semantic Spoofing*. Future IDS must evolve from analyzing packet headers (like MQTT/CoAP) to analyzing the "intent" of the communication. XAI will be vital here to explain why a specific semantic intent was classified as malicious.

D. Quantum-Resistant XAI-IDS

With the advent of quantum computing, the underlying cryptography of IoT protocols (e.g., TLS/DTLS used by CoAP) faces obsolescence. Integrating **Post-Quantum Cryptography (PQC)** with XAI-based IDS will be essential. Researchers must investigate how PQC-encrypted traffic affects the feature extraction process and whether XAI can still provide reliable "Human-in-the-Loop" insights when dealing with quantum-resistant data structures.

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E. Digital Twin Integration for Proactive Defense
6G will enable pervasive **Digital Twins** of IoT environments. A promising direction is the use of XAI to explain "What-If" scenarios within a digital twin. By simulating attacks on a virtual MQTT broker, the XAI-IDS can explain potential vulnerabilities before they are exploited in the physical world, moving from reactive detection to **Proactive Explainable Mitigation**.

VII. CONCLUSION

This paper has demonstrated that the "Black Box" nature of AI is no longer a prerequisite for high-performance IoT security. By combining **Pruned Random Forests** with **TreeSHAP**, we achieved a lightweight, transparent, and highly accurate IDS capable of protecting MQTT and CoAP protocols. As we move toward the 6G horizon, the marriage of efficiency and interpretability will remain the cornerstone of a trustworthy and resilient Internet of Things.

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