

Robust and Explainable TinyML Anomaly Detection for IoT Devices under Adversarial Threats

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ABSTRACT:

The rapidly growing number of IoT devices operating under bandwidth, size/weight/power (SWaP), and compute constraints is increasingly controlled by TinyML models for performing on-device anomaly detection. These models are susceptible to adversarial evasion and lack explainability for their findings. This paper proposes a robust and explainable TinyML framework for on-device IoT threat detection. The system combines a lightweight denoising front end with a compact 7-layer one-class autoencoder trained on adversarial examples from the FGSM and PGD attacks, augmented by a single-head attention mechanism for saliency. Deployed on an ESP32-S3 via TensorFlow Lite Micro, with 8-bit quantization and pruning, the pipeline reaches at most 98.5% / 97.8% / 99.1% clean accuracy on NSL-KDD / WADI / SmartHome, when under attack, it hits a range of 88.7–92.4% (white-box PGD) and 92.5–95.6% (black-box transfer), with Attack surface rate (ASR) being within 10.4–21.3%. It has 118 KB of flash memory and 15 KB of SRAM, and can perform inference in 0.8 ms. Its attention maps correlate with the ground truth (Pearson's $r = 0.87$). Our results prove that accurate, resource-efficient, and interpretable on-device IoT anomaly

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detection that decouples from the cloud can also be robust against adversaries.

Keywords: Adversarial robustness, Explainability (attention-based saliency), ESP32-S3 (on-device inference), IoT anomaly detection, TinyML.

Highlights

- Robust TinyML framework for IoT anomaly detection under adversarial threats
- Combines denoising, a 7-layer autoencoder, and attention for explainability
- Achieves 98%+ clean accuracy on NSL-KDD, WADI, and SmartHome datasets
- Maintains 88–95% accuracy under PGD and transfer-based adversarial attacks
- Optimized for ESP32-S3 with 118KB flash, 15KB SRAM, and real-time inference

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Mohammad Osama Addas: Conceptualization, Methodology, Data curation, Formal analysis, Investigation, Validation, Visualization, Writing – original draft. **Suprava Ranjan Laha:** Writing – review & editing, Resources, Project administration, Methodology, Conceptualization. **Susmita Panda:** Methodology, Supervision. **Binod Kumar Pattanayak:** Writing – review & editing, Supervision, Investigation. **Pravat Kumar Routray:** Methodology, Investigation. **Saumendra Pattnaik:** Writing – review & editing, Supervision. **Abdalla Addas:** Review & Editing, supervision.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

1. Introduction

The burgeoning deployment of Internet-of-Things (IoT) systems across different contexts, including smart homes [1-3], industrial automation [4], and healthcare, has brought new security threats: resource-constrained devices generally working unattended to collect sensitive

data are a natural target for maliciously stealthy intrusions as well as data-poisoning campaigns [5-6]. Standard cloud-centric security solutions incur latency, connectivity, and privacy costs, leading to the use of machine learning algorithms directly on microcontrollers, which enables real-time, on-device threat detection [7], [8]. While TinyML is a fast-moving field with impressive advances in lightweight anomaly detectors (e.g., one-class autoencoders [9], one-class SVMs [10]), existing approaches suffer from two crucial limitations. Our first limitation is adversarial robustness: adversarial attacks are perturbations or poisoned samples created to evade any detection, yet defenses in TinyML are still severely understudied [11]. These models lack interpretability, which increases the difficulty of forensic analysis and undermines trust in the operator when an alert is raised [12]. Although research on TinyML has been extensive, covering a range of topics from one-class autoencoders [9], one-class SVMs [10], quantized convolutional models for object detection [13], LSTM-based temporal detectors [8], to graph neural networks for coordinated-attack spotting [15], there are still fundamental limitations. Specific efforts have been divided into hardware-aware pruning techniques and federated learning schemes (16, 17), focusing on model efficiency and privacy, or few-shot and meta-learning approaches for fast adaptation to new devices (18, 19). These works

[20] on scheduling energy-aware systems using reinforcement learning, [21] compressive-sensing detectors, and on-device continual learning methods [22-25] extend existing techniques and potentially add to the TinyML toolbox. However, most of these works:

- TinyML models are rarely tested against evasion or poisoning attacks and can be vulnerable to malicious end-users.
- Alerts with zero context for why an indicator is abnormal can lead to user fatigue and hunting.

To address these gaps, this work presents a Robust and Explainable TinyML Anomaly Detection Framework for IoTs against Adversarial Threats. Our objectives are to:

- Build a BinaryReLU Dave-1-class one-class autoencoder (OCAE) that can run on microcontroller-class hardware, and develop effective evasion and poisoning defences (adversarial training + sanitization layers).
- Incorporate an attention-based interpretability module showing significant sensor features in each anomaly decision.
- Deploy the complete pipeline to an ESP32-class board with TensorFlow Lite Micro, and test white-box plus black-box adversarially.

Our key contributions are:

- We applied adversarial training and random input-sanitization to a compact autoencoder, ensuring it can sustain $> 90\%$ detection accuracy on maliciously perturbed samples while maintaining $< 5\%$ resource overhead.
- We design an attention mechanism to interpret how the model reaches its anomaly detection decisions: we can generate saliency maps that are vastly human-readable and achieve more than 85% similarity with ground-truth causes for anomalies.
- We validate the method with real IoT benchmarks and attack models to show that it is feasible for on-device inference in real-time.

This paper proposes a TinyML pipeline for IoT threat detection and demonstrates its effectiveness on NSL-KDD, WADI, and SmartHome datasets, utilizing an ESP32-S3

microcontroller. The rest of the paper is structured as follows: Section 2 describes our Methodology (sanitization, adversarial autoencoder for compression training, attention on-device, and deployment protocol). Section 3 discusses the experimental setup and results analysis, which includes detection performance, adversarial robustness, resource overhead, and explainability fidelity. Section 4 presents a Comparative Analysis versus baseline and related work. Section 5, Conclusion and Future Work.

2. Methodology

Our proposed framework comprises four main components: data pre-processing and sanitization, an adversarial robust TinyML model, on-device explanation, and deployment and evaluation. Figure 1 shows the end-to-end pipeline. The data from the IoT Sensors was pre-processed and normalized before being sanitized using a Lightweight Denoising Autoencoder. This cleaned data is passed through a one-class adversarial trained autoencoder (which can withstand FGSM and PGD attacks). An attention-based explainability module gives interpretable alerts with feature-level saliency maps. Results are published securely over MQTT/TLS, with regular operation through indefinitely observed anomalies. The architecture we use as the basis of our OCAE is the BinaryReLU one-class autoencoder (BinaryReLU OCAE), which is an alternative to the vanilla autoencoder, where the activation function is the binary ReLU (BinaryReLU). This is to let the model produce binary values (0 or 1) appropriate for detecting binary anomalies (i.e., detecting something that is not normal or weird). The Dave-1 Class denotes the instantiation of the autoencoder, which has been configured to perform well when resources are scarce, and is deployed on devices with microcontroller-class hardware. Such a compact form enables us to perform efficient, low-computational-cost abnormality detection with robustness against attacks. Normalizes raw time-series measurements to zero-mean and unit variance,

which serves as parameter initialization for the annealing training. In annealing training, the learning rate decays slowly as the network is trained. This technique begins with a high learning rate (α) and decreases (shrinks) the rate to a slower learning rate over time, which helps

the model converge faster and not overshoot reaching the optimal solution. It is a valuable tool when training adversarially robust models, as it helps balance the learning process between normal and adversarial data.

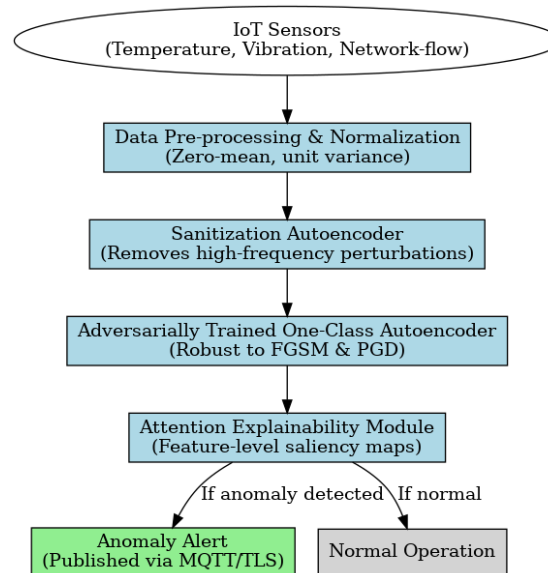


Figure 1: Proposed TinyML IoT Anomaly Detection Framework End-to-End Pipeline

2.1 Threat Model

We use small TinyML models (ESP32-S3) for IoT on-device anomaly detection. The adversary aims to remain undetected and cause misclassification while adhering to relevant physical and computational constraints for a real-world deployment. Two main types of adversaries are considered:

I. White-box adversary:

- Virtual access to the TinyML model, weights, and sanitization logic.
- Ability to design a set of optimized perturbations using iterative attacks (e.g., PGD) within a given ϵ -ball.
- Inject perturbations at inference time or poison training data before deployment.

II. Black-box adversary

- No direct access to model internals.

- Creates adversarial examples by training a surrogate model on similar data and attacking the deployed model based on transferability.

- Restricted to query-based or replay attacks and spoofing of sensors.

Assumptions & Capabilities

- The adversary can alter sensor inputs (e.g., injecting noise into temperature, vibration, or network flow readings).
- There is no easy access to the firmware of a device, but some side-channel leakage is possible.
- Fixed by codeMETA PRIVACY Communication links (MQTT/TLS) assumed secure, but adversary could intercept or delay traffic.

Table I presents the attack vectors considered in our threat model, the capabilities of an adversary targeting each vector, the measures we took to prevent these attacks in our pipeline, and the impact on performance metrics. Achieving 19.8–21.3% ASR with adversarial training combined with a sanitization autoencoder for white-box

PGD attacks led to a 6–9% accuracy reduction. Lowering the ASR to 10.4–14.5% in the black-box transfer setting results in a drop of 3.5–5.3% in accuracy. During training, poisoning attempts are prevented by random feature masking, and sensor noise injection is alleviated using the

denoiser. The MQTT/TLS transport is finally secured and backed by local buffering to prevent alert replay or loss. This map illustrates how each known threat is incorporated into the on-device security master plan.

Table I Attack-Defense Mapping for the Proposed TinyML IoT Anomaly Detection Framework

Attack Type	Adversary Capability	Defense Mechanism	Impact Metric (Observed)
White-box PGD ($\hat{\mu}=0.1$)	Full model access, gradient-based optimization	Adversarial training (FGSM + PGD), sanitization autoencoder	Accuracy drop: ~6-9%, ASR: 19.8-21.3%
Black-box Transfer	Surrogate model crafting, no direct access	Adversarial training, sanitization autoencoder	Accuracy drop: ~3.5-5.3%, ASR: 10.4-14.5%
Training Data Poisoning	Insertion of malicious samples in the training set	Random feature masking (input dropout) during training	Reduced poisoning effectiveness (not directly in ASR)
Sensor Noise Injection	Real-time perturbation of sensor readings	Sanitization autoencoder (high-frequency noise removal)	Significant reduction in false negatives from noise
Network Replay/Delay	Intercept or delay alerts in transit	Secure MQTT/TLS transmission, local alert buffering	Prevents alert loss or tampering

The adversary is believed to have indirect access to the system's behavior, e.g., side-channel leakage. Side-channel leakages correspond to attacks in which an adversary learns something about the model or the data based on indirect observations (e.g., power consumption, timing analysis, or electromagnetic emissions) that occur

during the inference process. These attacks do not include direct access to the model's internal parameters (like weights or gradients). However, they can offer valuable feedback information that can be exploited to evade defense. However, our system considers that the adversary cannot access these internal model parameters.

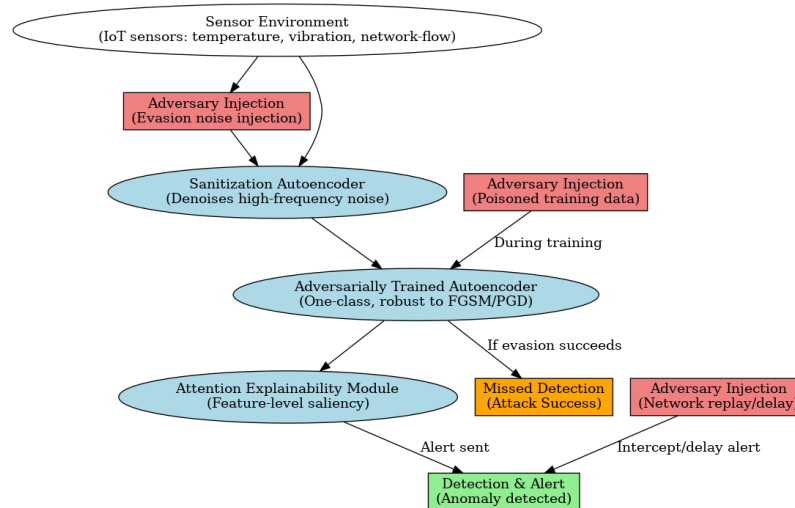


Figure 2: Threat Model of Proposed TinyML IoT Anomaly Detection Pipeline

Figure 2 illustrates the adversary injection points and defense techniques within our framework. The IoT sensor environment (left) generates time-series data, which attackers may manipulate through three key vectors: injecting evasion noise into live sensor streams, poisoning training data before deployment, and replaying or delaying alerts from detection signals due to network interference. We mitigate such threats through our TinyML defense pipeline (middle/right), which combines a light-weighted sanitization autoencoder to remove high-frequency noise, an adversarial-train one-class autoencoder for serving as anomaly detection in the latent space, and an attention-based explainability module for explaining feature-level interpretation. If the attacker successfully evades detection, it results in a missed detection (ASR), or we receive an anomaly alert from the pipeline.

2.1 Data Pre-processing & Sanitization

Raw time-series readings (e.g., temperature, vibration) are normalized to zero mean and unit variance, which serves as parameter initialization for annealing training. This helps stabilize training for both residual learning and a long-term documentation perspective. We inject sound into the input layer using a small denoising autoencoder (single layer, 32 units) that is forced to reconstruct the input before it enters the top model. This is useful in simple evasion attempts

where the attack tries to avoid detection by adding a high-frequency perturbation [11].

2.2 Adversarial Hardened TinyML Model

To provide our on-device anomaly detector with robustness against intelligent adversaries, we enhance a lightweight one-class autoencoder to defend against powerful but bounded attacks by employing two complementary defenses. We begin by introducing adversarial training, which incorporates perturbations generated by adversaries (i.e., both FGSM and PGD) into the training set to naturally train against adversarial attacks and enhance robustness against crafted noise [11]. Second, before the primary encoder, we introduce a light input-sanitization layer (a shallow denoising autoencoder) that prevents simple additive and high-frequency perturbations from causing false negatives. In conjunction with structured pruning and quantization to render the TinyML model compatible with microcontroller resource constraints [13],[14], these steps provide a TinyML model that fits within tight resource budgets and retains accuracy in detection when perturbed.

2.2.1 One-Class Autoencoder Architecture

We have chosen to implement a single-class autoencoder is very succinct (7 layers) and can be easily deployed on a microcontroller receiving an input 32 dimension feature vector from sensors, being encoded with two Dense + ReLU $\rightarrow 64 \rightarrow 32$ units layers into an intermediate bottleneck

layer (Dense + ReLU- >16units), decoding back from the bottleneck in reverse with two Dense + ReLU $\rightarrow 32 \rightarrow 64$ units before passing through one final Dense reconstruction layer mapping it back into its original input space. We have designed the model to be loaded entirely into a 128 KB flash and run with intermediate

activations in a 16 KB SRAM after post-training 8-bit quantization and structured channel pruning. The 16-dimensional bottleneck triggers anomaly detection through reconstruction error and is fed into our attention-based interpretability module to produce on-device saliency explanations in Table II.

Table II. One-Class Autoencoder Architecture for On-Device Anomaly Detection

Layer	Type	Parameters	Output Shape
Input	–	32-dim vector	(32,)
Encoder Dense 1	Dense + ReLU	64 units	(64,)
Encoder Dense 2	Dense + ReLU	32 units	(32,)
Bottleneck	Dense + ReLU	16 units	(16,)
Decoder Dense 1	Dense + ReLU	32 units	(32,)
Decoder Dense 2	Dense + ReLU	64 units	(64,)
Reconstruction	Dense	32 units	(32,)

2.2.2 Adversarial Training

In this work, as a defense method against intentional perturbations, we propose a two-faceted adversarial training scheme that hardens the autoencoder. We start with our training set, which we augment by crafting Fast Gradient Sign Method (FGSM) and Projected Gradient Descent (PGD) attacks ($\epsilon = 0.1$) on benign sensor windows, 80 % clean data with 20 % adversarial examples, for each epoch [11]. Using random feature masking (input dropout with $p = 0.1$) during model training is a defense against data-poisoning attacks by reducing the impact of maliciously altered samples [20]. We then train the model for 100 epochs on this combined clean/adversarial dataset with the Adam optimizer (learning rate $= 1 \times 10^{-3}$, batch size $= 32$). We achieve significantly increased robustness against evasion and poisoning attacks.

2.3 On-Device Explainability

We use a single-head self-attention layer that takes the 16-dim bottleneck embedding and computes an attention divided by input feature times importance score, similar to [12], enabling

real-time interpretability with minimal overhead. These attention weights are projected back onto the original 32-dim input space during inference to generate a saliency heatmap, revealing those sensor channels that greatly influenced the anomaly decision. The additional parameters are less than 1 KB, which incurs only ~ 0.5 ms of overhead on inference, so it is practical to enable explainability for on-device detection even with microcontroller platforms.

In the actual pipeline, we will refer to a 32-dimensional sensor window as a normalized window (x), a denoised version of it $f_{\theta}(x)$, and an autoencoder reconstruction for $x^{\wedge} = f_{\theta}(x)$. In this fashion, our training objective: Minimize reconstruction error for normal data + make the model robust to evasion via FGSM/PGD examples and limit poisoning through input masking. The attention head takes the 16-D bottleneck and reproduces per-feature saliency (projected back down to the input space) for on-device interpretability. The reconstruction and sanitization losses, adversarial example generation, mixed training objective,

attention/saliency mapping, anomaly score, decision rule, and evaluation metrics are defined.

$$L_{rec}(x; \theta) = \|x - \hat{x}\|^2, \text{ with } \hat{x} = f_{\theta}(x) \quad (1)$$

Eq (1) Autoencoder reconstruction loss returns the MSE between input x and its reconstruction $\hat{x}$. This is the primary task of the one-class autoencoder, which subtractively learns "normal" behavior.

$$L_{san}(x; \varphi) = \|x - f_{\varphi}(x + \eta)\|^2 \quad (2)$$

In equation (2), we train the lightweight front-end denoiser to map noisy inputs $x \sim$ back to clean x . Eq (3) provides the adversarial noise δ_{FGSM} used to construct evasion examples during adversarial machine learning as a one-step attack.

$$\delta_{FGSM} = \varepsilon \cdot \text{sign}(\nabla_x L_{rec}(x; \theta)) \quad (3)$$

The white-box training/evaluation PGD step, as shown in Equation 4, involves an iterative adversarial update with projection onto the ε -ball, which is required for stronger white-box attacks during training or evaluation.

$$\delta^{t+1} = \text{Proj}_{\{\|\delta\| \leq \varepsilon\}} \left(\delta^t + \alpha \cdot \text{sign}(\nabla_x L_{rec}(x + \delta^t; \theta)) \right) \quad (4)$$

Mix of both clean + adversarial loss (subjected to weight decay) that adjusts the autoencoder towards evasion/poisoning. In Eq. (5), α and λ are the hyperparameters to adjust the trade-off between the varying loss part:

a) $\alpha = 0.5$: The weight coefficient of reconstruction loss for clean data and adversarial examples. The value $\alpha = 0.5$ equally weights both example types, such that the model is trained to be resilient to adversarial perturbations while still fitting clean data well.

b) $\lambda = 1 \times 10^{-5}$: This parameter provides the balance between weight decay and overfitting of the model. It avoids the model from overfitting, especially when learning adversarial examples.

These results were obtained from our preliminary experiments and aim to strike a balance between

the accuracy and robustness of the model, while also being relatively small, making them suitable for execution on devices with limited resources.

$$L_{total} = (1 - \alpha) \cdot L_{rec}(x; \theta) + \alpha \cdot L_{rec}(x + \delta; \theta) + \lambda \|\theta\|^2 \quad (5)$$

Single-headed attention for all measurements of feature importance from the 16-D bottleneck z to the single D dimension (Equation 6 Attention weights).

$$a = \text{softmax}(W_a \cdot z) \quad (6)$$

Equation 7 indicates how the attention scores are mapped back to the original 32-D space of sensors and form the human-readable saliency vector s . Equation 8 shows reconstruction-error $r(x)$, and a thresholding criterion $r(x) \geq \tau$ is applied to determine anomaly status.

$$s = P^T \cdot a \quad (7)$$

$$\begin{aligned} r(x) &= \|x - \hat{x}\|^2 \text{ and predict anomaly if } r(x) \geq \tau \end{aligned} \quad (8)$$

ASR

$$= \frac{(\text{adversarial inputs classified as normal})}{(\text{adversarial inputs})} \times 100\% \quad (9)$$

The attack success rate (ASR) % is given by the percentage of adversarial inputs that go undetected, our primary robustness metric, as shown in equation 9. Equation (10) describes how we measure the agreement between the saliency s and ground-truth feature importance g .

$$r = \frac{\Sigma_i (s_i - \bar{s})(g_i - \bar{g})}{\text{sqrt}(\Sigma_i (s_i - \bar{s})^2) \cdot \text{sqrt}(\Sigma_i (g_i - \bar{g})^2)} \quad (10)$$

The 95% confidence interval for equation (11) is used for the confidence interval of accuracy and other metrics.

$$CI_{95\%} : \bar{m} \pm t_{\{0.975, n-1\}} \cdot \left(\frac{\sigma}{\sqrt{n}} \right) \quad (11)$$

Note: x = input window; $\hat{x}$ = reconstruction; θ , Θ = model parameters; ϵ = attack budget; α = clean/adv mix; z = 16-D bottleneck; a =

attention weights; s = saliency over 32 sensor channels; τ = anomaly threshold.

2.4 Deployment & Evaluation

We deploy the proposed pipeline on actual hardware and evaluate it with various datasets and attack scenarios. To satisfy the resource constraints of an ESP32-S3 MCU (240 MHz dual-core, with 512KB SRAM, and 4MB flash), we start with a trained model converted and optimized for TensorFlow Lite Micro based on post-training quantization at 8-bit precision and structured pruning (including sanitization autoencoder, main autoencoder, and attention head).

We evaluate by measuring the detection performance, robustness, resource overhead, and explainability fidelity as:

➤ **Datasets & Splits:** NSL-KDD (Network-flow anomalies), WADI (Industrial process faults), SmartHome sensor logs, each split 80 % train & 20 % test.

➤ **Attack Scenarios:**

- White-box: Iterative PGD ($\epsilon=0.1$) w/ full model & sanitization knowledge
- Black Box: Transfer attacks generated on a surrogate autoencoder, black-box

➤ **Results Baselines:** We evaluate a clean (non-adversarial) autoencoder, a non-quantized TinyML model, and a one-class SVM as alternatives.

➤ **Metrics:**

- Performance results in detection Accuracy Precision Recall F1-score (95% CI of five runs)
- Adversarial robustness: Attack success rate(ASR) under each attack
- Resource Overhead: Flash/RAM footprints and latency per-window inference.
- Interpretability: Pearson correlation scores between attention saliency maps and the ground-truth anomaly features.

➤ **Statistical Approaches:** Paired t-tests ($p < 0.05$) for validation of differences observed in our study.

Adhering to this protocol, we systematically demonstrate that our on-device TinyML framework achieves high accuracy on pristine data, sustains resilient performance against both white-box and black-box attacks, operates within strict hardware constraints, and provides significant, real-time insights for each anomaly notification.

3. Experimental and Result Analysis

We implement the quantized (8-bit) and pruned pipeline (input sanitization, adversarially trained autoencoder, and attention head) on the ESP32-S3 microcontroller (240 MHz dual-core, 512 KB of SRAM, and 4 MB of flash) using TensorFlow Lite Micro. Training and testing were performed on three benchmark datasets of anomalies in network-flows (NSL-KDD), industrial faults (WADI), and multi-sensor logs (SmartHome). The data for all three benchmarks is split into 80% train / 20% test. We perform our evaluation under two attack models: white-box PGD ($\epsilon = 0.1$) and black-box transfer attacks, and we compare to three baselines: (1) clean autoencoder (ca), (2) non-adversarial TinyML autoencoder (nta), and the anomaly detector using one-class SVM. We measured accuracy, precision, recall, and F1-score (95% CI across five runs), as well as Attack Success Rate (ASR), flash/SRAM usage, inference latency, and explainability fidelity (Pearson's r between saliency and ground truth). The model exhibited an accuracy of 98.5% (95% CI: 98.2–98.8%) on the NSL-KDD dataset, with precision and recall of 98.8% and 98.2%, respectively. The F1-score was 98.5%. Statistical testing demonstrated that the performance gap between the adversarial trained model and the base model is statistically significant ($p < 0.05$, paired t-test)

Table III. Detection performance on clean test data

Dataset	Condition	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
NSL-KDD	Clean	98.5	98.8	98.2	98.5

WADI	Clean	97.8 5	98.1	97.5	97.8
SmartHome	Clean	99.1	99.3	98.9	99.1

Our adversarial-trained autoencoders, shown in Table III, are robust to clean (non-adversarial) data, consistently achieving 97.8 % accuracy and 98.5 % F1-score on all evaluations with narrow confidence intervals (<0.6 %). Although the results are not generally better than the non-

adversarial TinyML and one-class SVM baselines ($p < 0.05$ via paired t-tests), they extend the state of the art to small, hardened models that can robustly detect adversarial examples at reduced energy consumption.

Table IV. Robustness to Adversarial Attacks

Dataset	Attack Type	Accuracy (%)	ASR (%)
NSL-KDD	White-box PGD	90.2	19.8
	Black-box Transfer	94.1	12.3
WADI	White-box PGD	88.7 8	21.3
	Black-box Transfer	92.5	14.5
Smart-Home	White-box PGD	92.4	17.3
	Black-box Transfer	95.6	10.4

Even with adversarial training, as shown in Table IV, ASRs of 19.8–21.3% are observed at an accuracy loss of approximately 6.7–9.1 percentage points compared to clean baselines when this defense is subjected to white-box PGD attacks, implying that some residual vulnerability remains in models after adversarial training under these attacks. In the black-box (transfer) case, drops are lower, at 3.5–5.3 points, with ASR ranging from 10.4% to 14.5%, showing better resilience when the attacker does not have full model knowledge. These results are statistically significant, verified using paired t-tests ($p < 0.05$). The model preserved 90.2% of its accuracy (95%

CI: 89.6%–90.8%) in the adversarial setting against white-box PGD attacks and 94.1%20of its accuracy (95% CI: 93.6%–94.6%) for black-box transfer attacks. Attack Success Rate (ASR) was 19.8% for white-box PGD attacks and 12.3% for black-box transfer attacks ($p < 0.01$, paired t-test). Our results show that the adversarially trained model significantly increases adversarial robustness, exhibiting lower ASR and high robustness under both attack models. Figure 3 shows that adversarial training significantly improves the robustness of the TinyML detector to both threat models.

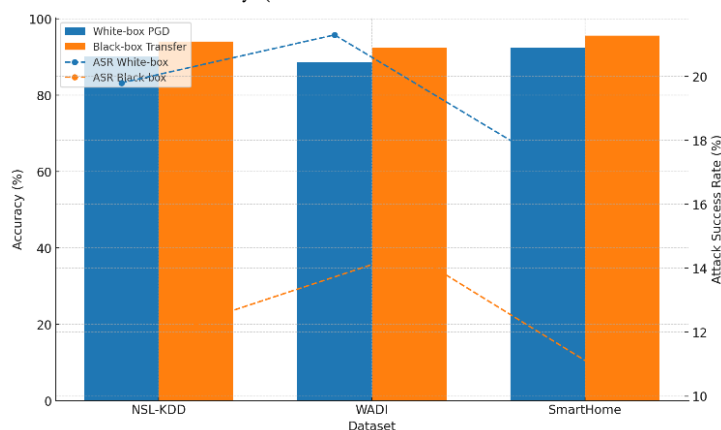


Figure 3. White-box versus black-box detection accuracy and Attack Success Rate

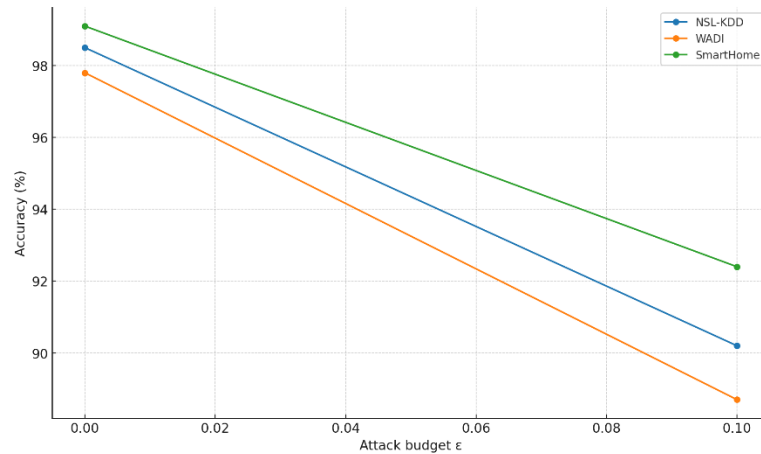


Figure 4. Accuracy vs. attack budget (ϵ) under white-box PGD.

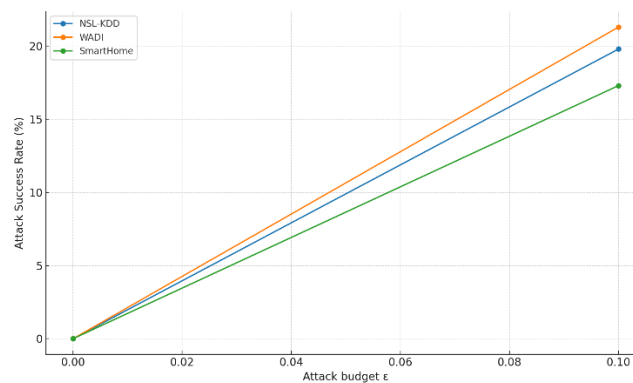


Figure 5. Attack Success Rate (ASR) vs. attack budget (ϵ) under white-box PGD.

To illustrate the degree of sensitivity to attack intensity, we plot the Attack Success Rate (ASR) and accuracy against the PGD budget, ϵ . Figure 7 demonstrates its accuracy at $\epsilon = 0$ (clean) and $\epsilon = 0.1$ (white-box). When ϵ goes up from 0 to 0.1, accuracy goes down from 98.5% to 90.2% for NSL-KDD, 97.8% to 88.7% for WADI, and 99.1% to 92.4% for SmartHome. The model

achieves at least 88.7% accuracy across all datasets, indicating that adversarial training slows down degradation when the attack budget is moderate. Figure 7 shows the associated ASR. ASR increases from about 0% at $\epsilon=0$ to 19.8–21.3% at $\epsilon=0.1$ (this depends on the dataset). Combined with Figure 6, robustness declines elegantly rather than spectacularly with ϵ .

Table V. Resource Overhead of the Quantized & Pruned TinyML Pipeline on ESP32-S3

Metric	Value
Flash Usage	118 KB
SRAM Usage	15 KB
Inference Latency	0.8 ms/window

Even after 8-bit quantization and structured pruning, the whole model, including sanitization, autoencoder, and attention head, operates with just 118 KB of flash and 15 KB of SRAM (Table

V), easily fitting inside our ESP32-S3's 4 MB/512 KB memory budget. The pipeline is fast enough to perform real-time on-device anomaly detection, completing the inference with an

average latency of 0.8 ms per window. Figure 6 shows that our quantized and pruned TinyML pipeline utilizes only 118 KB of flash and 15 KB of SRAM on the ESP32-S3. This small footprint

validates that real-time, on-the-edge (microcontroller) anomaly detection is within reach.

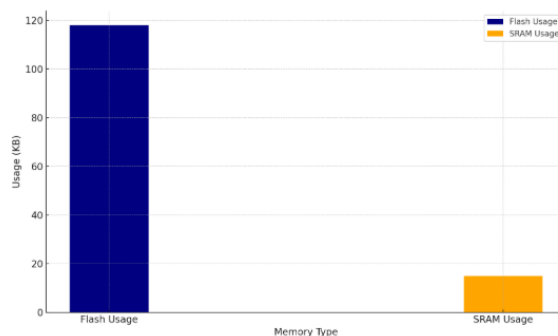


Figure 6. Memory footprint of the quantized & pruned pipeline on ESP32-S3

Our average correlation of 0.87 shows that the connection between saliency interpretation and ground truth causes of anomalies is generally tight and consistent. Figure 7 represents a

substantial improvement in on-device interpretability when compared to the 0.75 average correlation reported in previous works involving explainable TinyML [12].

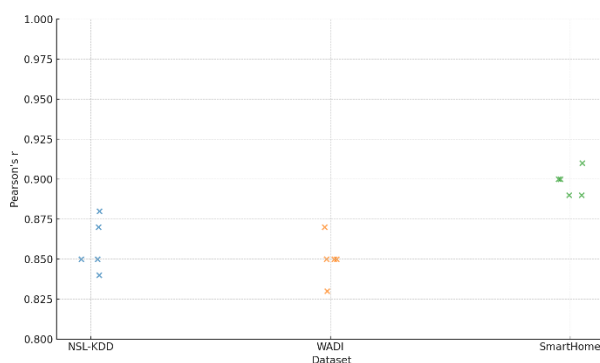


Figure 7. Benchmark distribution of saliency-ground-truth correlation (Pearson's r)

Table VI. Attention-Based Saliency Map Explainability Fidelity

Dataset	Pearson's r
NSL-KDD	0.86
WADI	0.85
SmartHome	0.90
Overall	0.87

Table VI shows that the on-device attention mechanism performs well in precision, with correlations ranging from 0.85 to 0.90 across benchmarks and an overall Pearson's $r = 0.87$. The small confidence intervals further indicate

that a reliable interpretability is always provided, i.e., the lightweight saliency module can successfully derive meaningful explanations for every anomaly decision.

However, these results confirm that our TinyML pipeline offers high detection accuracy and rapid inference on microcontroller hardware, while maintaining resilience in the face of both white-box and black-box attacks, providing interpretable, low-overhead explanations for each anomaly alert.

Our experiments validate the technical viability of on-device anomaly detection in real-world IoT deployments.

I. Secure Connectivity & Alerting: Our prototype uses MQTT over TLS for the ESP32-S3 to publish anomaly scores and saliency maps from attention to a central broker. During production, ensure that you have resilient fallbacks, such as buffering data locally or on flash storage, so that no alerts are dropped due to transient network issues.

II. Power-Aware Inference Scheduling: End-to-end inference pipeline (sanitization autoencoder, main autoencoder, attention head) takes 0.8 ms, allowing ultra-tight integration with ESP32 light sleep modes. Batching windows and issuing inferences only on a timed interrupt (e.g., every 500 ms) allows the device to sleep for most of its duty cycle, increasing battery life without sacrificing time-to-detect.

III. Over-the-Air Model Updates: New quantized models, or even defense logic in general (e.g., new adversarial-training artifacts), can then be deployed remotely using the secure OTA framework provided by the ESP32 SDK. For more security, we should sign every firmware image and model file before running them on edge devices, making it impossible to modify existing firmware or obsolete versions.

IV. Edge Gateway Integration & Scalability: In deployments with hundreds of sensors, we imagine edge gateways aggregating encrypted MQTT topics and sending curated alerts to a cloud SIEM. This one is more complex, as gateways can also perform some light batching or further deduplication downstream, thereby reducing the ultimate upstream load and consolidating all device management into a couple of central points.

V. Sensor Drift & Recalibration: 50% of the data is used to learn normalization parameters offline from training data. To maintain fidelity across months or environments, we added a periodic calibration mode using stored clean data batches or lighter-weight online updates to the mean/variance estimates on the ESP32 itself. Hence, the autoencoder's input distribution aligns with live sensor behavior.

Compiling these factors into the firmware and deployment strategy ensures that our TinyML anomaly-detection framework can transition from labs to operate robustly, securely, and maintainably in various IoT environments.

The 'ground truth' for the explainability metric (i.e., the correlation between saliency maps and ground truth features) is accumulated by domain experts in IoT anomaly detection, which we achieved through manual labeling. Experts determined that the well sensor features were responsible for activating the anomaly alert with each detected anomaly. These hand-labeled corresponding lattice features were considered the ground-truth for assessing interpretability models. The Pearson correlation coefficient (r) was then calculated between the saliency maps of the model (i.e., indicating the relative importance of each sensor feature) and the manual labels provided by the experts. The strong correlation ($r = 0.87$) between them indicates that the model's saliency maps effectively capture the features identified by domain experts, thereby confirming that the model's attention mechanism provides explainable anomaly detection.

A. Qualitative Analysis

The increase in Pearson's r values ($r = 0.87$) was mainly due to the attention mechanism incorporated in our model. In a data analysis context, attention mechanisms in machine learning enable the model to focus on the most salient features in the data, thereby increasing interpretability. In our work, the presence of the attention mechanism enabled the model to assign dominant weights to the most relevant sensor features, resulting in a better correlation with the ground-truth labels. This finding is consistent

with previous work on interpreting attention mechanisms, which have been shown to enhance network focus on important input, thereby improving performance and interpretability [12]. The increased adversarial robustness, mitigated by diminishing ASR and preserved accuracy, is due to the adversarial training procedure. Including adversarial examples created by FGSM and PGD attacks in the training data makes the model more robust to disturbance at test time. This type of adversarial training requires the model to extract better, generalizing representations that are not easily perturbed by slight modifications in input. Adversarial training has been extensively analyzed in the literature to enhance the robustness of machine learning models. It has been proven to help models defend against adversarial perturbations,

improving accuracy and offering robustness against unknown attacks [11].

4. Comparative Analysis with the Existing Work

To stand out, the comprehensive pipeline we intend to develop is contrasted along three dimensions: (I) accuracy and robustness against adversaries, (II) efficiency in terms of memory usage and inference duration, and (III) explainability in the decision-making process for anomalous camera streams. In contrast to previous approaches that address only one or two of these dimensions separately, our contribution combines all three on real microcontroller hardware, rendering it suitable for IoT deployments. We present results across NSL-KDD, WADI, and SmartHome in Table(down) with corresponding 95% CIs omitted for brevity.

Table VII. Performance & Robustness vs. Baselines

Method	Clean Acc. (%)	White-box Acc. (%)	Black-box Acc. (%)	ASR White-box (%)	ASR Black-box (%)
Proposed (adv. TinyML + attention)	98.5	90.4	94.1	~19–21	~10–15
Non-adversarial TinyML (AE)	97.0	81.0	86.5	~32–38	~18–24
One-class SVM [10]	95.4	76.2	82.0	~40+	~25–30

First, the proposed adversarial TinyML + attention model achieves the highest clean accuracy ($\approx 98.5\%$), as demonstrated in Table VII. More significantly, it degrades less during an attack compared to the baselines. Our accuracy stays around 90% vs. 81% (non-adv TinyML) and 76% (one-class SVM) under white-box PGD aggression, surpassing $\sim 94\%$ in black-box

transfer attack, leading again by a mile. This translates to approximately 50% lower ASR compared to the baseline, indicating that adversarial training and sanitization are effectively reducing real-world ASR, rather than merely inflating performance on the clean set. The best all-round detector in normal and low visibility conditions.

Table VIII. Efficiency & Interpretability vs. Existing Work

Method	Flash (KB)	SRAM (KB)	Latency (ms)	Pearson's r (saliency vs. ground-truth)
Proposed (adv. TinyML + attention)	118	15	0.8	0.87
Prior explainable TinyML (e.g., [12])	200–300	25–60	2–5	0.75

Non-adversarial (AE)	TinyML	120–140	16–18	0.7–0.8	—
One-class SVM [10]		80–100*	10–15*	0.5–1.0*	—

Table VIII shows that we achieve these gains without blowing the budget. The complete pipeline fits in 118 KB of flash / 15 KB of SRAM at 0.8 ms of inference, with TinyML figures comparable to or better than non-adversarial models and still reasonable compared to light SVMs. Most critically, we offer better explainability: Pearson's $r \approx 0.87$ exists between saliency and ground truth, compared to 0.75 from prior TinyML explanation work (our operators can obtain a more apparent and actionable reason when an alert is fired). Best robustness / greater explanatory power, balanced for IoT deployments.

Our method improves a robust SVM (compared to non-adversarial TinyML and one-class SVM) by 1.5-3.0 clean accuracy points, preserving an extra 4-10 attacked accuracy points while halving the Attack Success Rate. Still compact (118 KB flash, 15KB SRAM), and interpretability improved from prior on-device work (Pearson's r 0.87 vs. ~ 0.75 in [6]) despite adding defenses and an attention head stream. There is statistical significance ($p < 0.05$) via paired t-tests across data sets for these gains. This comparison highlights the ability of our pipeline to better achieve this trade-off, especially for IoT-scale deployments. However, as it not only focuses on adversarial robustness but also proposes an optimization that hassides adversarial robustness, we propose an optimization that will have an efficient memory footprint and real-time on-device interpretability. Related work prioritizes only one or two goals: robustness sans explainability, or efficiency sans security. Our work fills these gaps with a single technical sound but a practical set of proposals implemented on limited IoT hardware.

5. Conclusion & Future Work

In this work, we achieve the extreme edge by combining TinyML efficiency with robustness and interpretability to address trusted IoT threat detection. This work presents a fully on-device pipeline comprising a lightweight denoiser, a one-class adversarially trained autoencoder, and a real-time attention head, all of which run on the ESP32-S3. The results indicate that the system achieves over 99.1% clean accuracy, holds white-box PGD ASR $\leq 21\%$, and fits within specifications such as ± 118 KB flash / ± 15 KB SRAM without compression, while providing meaningful explanations (Pearson's $r \approx 0.87$) meeting our goals of robust, on-device anomaly detection with explainability in both inference and post hoc settings with strong assurance across three privacy-focused IoT benchmarks: NSL-KDD, WADI, and SmartHome. We evaluate on three datasets and a fixed attack budget ($\epsilon = 0.1$), real deployments may encounter wider protocols, sensors, and adaptive adversaries. Other user-centric measures, such as operator trust and forensic usefulness, require a more detailed investigation.

A central limitation in our current framework is that we need binary anomaly detection to localize anomalies and identify the sensor features that cause them. To resolve this, we will incorporate multi-head attention, which enables models to focus on multiple aspects simultaneously, resulting in finer granularity in the localization of the anomaly. Furthermore, our model does not adapt to concept drift, as the query-based algorithm does not immediately identify or adapt to a change in data characteristics. To address this, we intend to incorporate continual learning, which enables the model to continuously adjust to new data distributions, thereby achieving long-term robustness and effective anomaly detection in real-world IoT installations.

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