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A Zero-Trust Enabled Adaptive Intrusion Detection Framework for Resource-Constrained Internet of Things Networks

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Abstract: The fast-growing number of Internet of Things (IoT) deployments has changed the digital landscape. However, the distributed and heterogeneous nature of IoT networks enlarges the attack surface by exposing critical systems to botnets, distributed denial-of-service attacks, spoofing, and moving laterally. Tra- ditional perimeter-based security measures and deep learning- based intrusion detection systems, which are too resource- demanding, are not applicable to the resource-constrained IoT context. This paper presents the Adaptive Intrusion Detection Framework (ZTA-AIDF) we have put together which is for IoT gateways and edge nodes. This framework includes light weight statistical traffic profiling, entropy based anomaly quantification, hybrid ensemble learning, and dynamic trust recalibration which in turn provides continuous verification with minimal computa- tional impact. We differ from static IDS models which do not adapt over time our put forth approach includes behavioral drift detection and adaptive weight optimization to maintain security against new attack trends. Also we report that in preliminary analysis we out perform traditional anomaly detection in terms of stability of detection and in reduction of false positive reports. Our framework is to fill in the gap between zero trust security and lightweight intrusion detection for the scale of today's IoT.

Index Terms: Internet of Things, Zero Trust Architecture, In- trusion Detection System, Adaptive Security, Ensemble Learning, Edge Security, Network Anomaly Detection.

I. INTRODUCTION

In the field of distributed computing we see a transformation with the Internet of Things (IoT) which is that of connection of billions of devices which are able to communicate inde- pendently. In smart health care systems, industrial automation, and intelligent transport networks' fields we see that IoT has become a basic element of today's infrastructure. Although we have made great progress with the IoT we also see that they are very much at risk because of what we see as low security at the device level, weak identification methods, and also limited computing power.

Traditional security methods which put great stock in peri- metrical defense measures that assume an internal network is secure are for the most part what we see today. That which is accepted as true no longer stands in the case of IoT which has within it elements that are at all times untrustworthy. Also, in the field of IoT we see a very large issue in that which is supposed to be protected by security measures which in fact do not have the resources computational in this case to put in place complex intrusion detection systems like those that use heavy encryption or deep neural networks.

Recent we've seen that which machine learning has brought to the table in terms of an improvement in the performance of anomaly detection in traditional enterprise networks. That said these solutions do still assume we have at our disposal plenty of compute power and also that network behavior is fairly static. In the case of IoT networks we see the opposite, they are very much in a state of flux, we see great diversity in the types of devices which are present and also that which we see as normal changes very often. Also what we have in Zero Trust Architecture is a security which doesn't play into the idea that some entities are more trusted than others. In fact it is a model which constantly questions the trust of all entities. While zero trust has won over in the cloud and enterprise spaces it's integration with what we might term lightweight intrusion detection for the IoT setting is still a very under researched area. This paper presents a unique framework called the Zero- Trust Enabled Adaptive Intrusion Detection Framework (ZTA- AIDF) which combines a dynamic trust evaluation with a computationally lightweight ensemble learning technique. The proposed framework is intended for IoT gateway level de- ployment, offering adaptable protection while conserving edge computing hardware resources

The remainder of this paper is organized as follows. In Section II, we survey the literature on IoT intrusion detection and zero-trust security. Section III discusses the gaps in the literature, while Section IV summarises the contributions of the paper.

II. LITERATURE REVIEW

Signature based systems use pre defined attack patterns. In that which is computational in nature these do well but they fail to identify new or polymorphic attacks. In the IoT which is a very dynamic space static signature databases which are the basis of these systems quickly become out of date.

Statistical anomaly based models look at what has changed in traffic patterns which may include packet rate variance, entropy changes, or connection frequency. While more flexible than signature based approaches they also see a great deal of success in false positive identification which in the ever changing IoT environment is a large issue.

Deep in the field of IDS we see that CNN, RNN, and Autoencoders which are based in deep learning have done very well in benchmark studies. But in the IoT gateways' world we see less of their use because of high memory and processing needs. Also deep learning models are very prone to adversarial attacks and do not have much interpretability.

Only a limited number of studies have tried to combine adaptive intrusion detection with dynamic trust evaluation in IoT networks. Most existing frameworks focus on treating trust management and intrusion detection as disparate systems instead of integrated systems. Furthermore, there has been a lack of focus on managing concept drift in IoT traffic patterns.

Therefore, there exists a need for a unified framework that combines:

1) Lightweight anomaly detection
2) Dynamic trust scoring
3) Adaptive weight recalibration
4) Concept drift resilience
5) Zero-trust verification principles

III. RESEARCH GAP ANALYSIS

In present studies we note the following research gaps:

1) Lack of IDS models which are lightweight and for the IoT gateways' specific issues.
2) We see a gap in which zero trust elements are not well integrated with intrusion detection.
3) Also we have little to no focus on behavioral change in IoT networks.
4) Also we see that deep learning based IDS has high computational requirements
5) Also there is a lack of a unified framework which puts trust management and anomaly detection together.

To close these gaps we need a framework that puts into balance computational efficiency with adaptive security.

IV. MAJOR CONTRIBUTIONS

Here is what this research put forth:

1) Design of an adaptive intrusion detection system which is Zero Trust enabled for IoT gateways with constrained resources.
2) We present light weight statistical traffic profiling and hybrid ensemble learning.
3) Also we have developed a dynamic trust model for continuous device validation.
4) We introduce behavioral drift detection for adaptive model update.
5) We did a technical assessment of computational perfor- mance for edge deployment.

V. SYSTEM MODEL AND NETWORK ASSUMPTIONS

We consider an IoT ecosystem consisting of a set of heterogeneous devices

$$D = \{d_1, d_2, \ldots, d_n\}$$

connected through an edge gateway G. Each device generates network traffic flows

$$F = \{f_1, f_2, \ldots, f_m\}$$

In each flow we present statistical metadata features instead of payload level inspection.

We assume the gateway has limited computational resources which in this case may be a single board computer (for example an ARM based edge device) with restricted memory and CPU capacity. Thus heavy deep learning inference is ruled out for real time deployment.

Traffic features we extract per flow include:

$$x = \{x_1, x_2, ..., x_k\}$$

where:

- x_1: Mean packet size
- x_2: Flow duration
- x_3: Packet inter-arrival variance
- x_4: Source IP entropy
- x_5: Protocol distribution ratio
- x_k: Connection frequency metric

The objective of the detection framework is to classify each flow as:

$$y \in \{0, 1\}$$

where 0 represents normal behavior and 1 represents malicious behavior.

VI. PROBLEM FORMULATION

Let:

$$X \in R^{m \times k}$$

represent the feature matrix of m flows and k extracted features.

The detection model is defined as a function:

$$F : R^k \rightarrow \{0, 1\}$$

The goal is to minimize classification error:

$$\min \; L(F(X), Y)$$

subject to computational constraints:

$$C_{cpu} \leq C_{max} \; M_{memory} \leq M_{max}$$

where:

- C_{cpu} = runtime CPU utilization
- M_{memory} = memory consumption

Thus in this case what we have is a constrained optimization problem which balances accuracy and computation feasibility.

VII. HYBRID ENSEMBLE DETECTION MODEL

The proposed ensemble consists of three classifiers:

$$F(x) = \overset{3}{\underset{i=1}{}} \; w_i f_i(X)$$

Where:

- $f_1(x)$: Random Forest
- $f_2(x)$: Gradient Boosting
- $f_3(x)$: One-Class SVM

Weights are dynamically recalibrated based on recent per- formance:

$$w_i^{t+1} = \frac{1 - e^t_i}{{}^3{}_{j=1}(1 - e^t_j)}$$

where e^t_i represents recent error rate in sliding window t.

This adaptive approach which we put in place also sees to it that we do away with performance drop out as traffic behavior changes.

VIII. DYNAMIC TRUST EVALUATION MODEL

Each device d is assigned a trust score T_d:

$$D = |E_{current} - E_{previous}|$$

where:

- $0 < \alpha < 1$ is smoothing factor
- $S_d^{behavior}$ = normalized anomaly score

If:

$$T_d < \tau$$

device d is isolated or put in a separate network segment per zero trust policy.

IX. CONCEPT DRIFT DETECTION

To handle evolving IoT traffic, we monitor drift using:

$$D = |E_{current} - E_{previous}|$$

If:

$$D > \delta$$

retraining is triggered.

Alternatively, KL-divergence between distributions is com- puted:

$$D_{KL}(P||Q) = \quad P(x)\log\frac{P(x)}{Q(x)}$$

where P and Q represent historical and current traffic distributions.

X. PROPOSED ARCHITECTURE

We present the Zero Trust Enabled Adaptive Intrusion Detection Framework (ZTA-AIDF) which we deployed at the IoT gateway level. The architecture we have put forth is made up of five functional modules:

1) Traffic Monitoring Engine
2) Feature Extraction Unit
3) Hybrid Detection Core
4) Trust Management Module
5) Policy Enforcement Engine

A. Traffic Monitoring Engine

This module collects packets passively and collects meta- data and timestamps, source and destination addresses, proto- cols and flows. To reduce overhead and maintain privacy, we do not perform deep packet inspection.

B. Feature Extraction Unit

Raw traffic is processed into condensed statistical represen- tations. The approach to dimensionality reduction means that complexity for feature extraction is linear to the volume of the processed traffic.

C. Hybrid Detection Core

The aggregate model which puts forward what is best from tree based classifiers and anomaly detection models' fea- tures. We have moved away from majority voting to adaptive weighted fusion which in turn improves the model's stability during drift.

D. Trust Management Module

Each IoT device has a trust profile which is an ongoing record of its behavior. Trust in devices is re evaluated which in turn takes away from a compromised device any high privilege it may have obtained.

E. Policy Enforcement Engine

When trust scores go down beyond a certain point we see to it that suspicious nodes are isolated. This may include VLAN reconfiguration, firewall rule changes, or session break off.

XI. EXTENDED ALGORITHM DESCRIPTION

Algorithm 1 Zero-Trust Adaptive Intrusion Detection Frame- work

```
1:  Initialize ensemble classifiers and trust table
2:  while n do
      etwork is active
3:    Capture traffic metadata
4:    Extract statistical features
5:    Compute ensemble anomaly score
6:    Update sliding window error rates
7:    Recalculate adaptive weights
8:    Update device trust scores
9:    if trust score <  threshold then
10:       Trigger isolation policy
11:   end if
12:   Check drift condition
13:   if drift detected then
14:       Retrain ensemble model 15:    end if
16: end while
```

The algorithm functions in streaming mode and does not conduct batch reprocessing on historical data, which preserves real time efficiency.

XII. COMPUTATIONAL COMPLEXITY ANALYSIS

Let:

- n = number of traffic flows
- k = number of features
- t = number of trees

A. Random Forest

Time complexity:

$$O(t \cdot n \log n)$$

B. Gradient Boosting

Time complexity:

$$O(m \cdot n)$$

where m represents boosting iterations.

C One-Class SVM

Training complexity:

$$O(n^2)$$

However, inference complexity remains:

$$O(n)$$

Given that feature dimension k system complexity is kept reasonably low, making it appropriate for edge devices.

XIII. SCALABILITY ANALYSIS

Consider a case where the network grows from n to 2n devices
Feature extraction complexity increases linearly:

$$O(n)$$

Trust management complexity increases linearly, as each device holds a separate trust score.

There is no need for a central unit to perform any heavy computations, which facilitates horizontal scalability for mul- tiple gateways.

XIV. EXPERIMENTAL EVALUATION

A. Dataset Description

To assess the proposed ZTA-AIDF framework, experiments were performed with a hybrid IoT intrusion dataset built from both benchmark IoT traffic trace dataset and attack patterns that were synthetically injected. The dataset includes both attack and benign traffic flows with a variety of IoT devices such as smart sensors, cameras, and embedded controllers.
The dataset includes the following attack types:

1) Distributed Denial-of-Service (DDoS)
2) Brute Force Authentication Attempts
3) Botnet Command and Control Communication
4) IP Spoofing
5) Port Scanning

Total traffic instances: 120,000 flows Malicious instances: 38,500 Benign instances: 81,500

Class imbalance ratio:

$$IR = \frac{\text{Benign}}{\text{Malicious}} = 2.11$$

To mitigate imbalance bias, the stratified sampling was applied during the training process.

B. Statistical Feature Profiling

Mean packet size distribution (benign):

$$\mu_{benign} = 512.4 \text{ bytes}$$

Mean packet size distribution (malicious):

$$\mu_{attack} = 948.7 \text{ bytes}$$

Entropy comparison shows higher variance in the spoofing and botnet phases, validating entropy's usefulness as a discriminative feature.

C. Experimental Environment

All experiments were carried out in an edge-gateway sim- ulation environment:

1) Raspberry Pi 4 (4GB RAM)
2) Quad-core ARM Cortex-A72 CPU
3) Python-based implementation
4) Scikit-learn ensemble implementation

Training was conducted offline, and inference was per- formed in real-time streaming mode.

XV. EVALUATION METRICS

The following metrics were used:

A. Accuracy

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

B. Precision

$$\text{Precision} = \frac{TP}{TP + FP}$$

C. Recall

$$\text{Recall} = \frac{TP}{TP + FN}$$

D. F1-Score

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

E. False Positive Rate (FPR)

$$FPR = \frac{FP}{FP + TN}$$

F. Area Under Curve (AUC)

AUC was calculated from the Receiver Operating Charac- teristic (ROC) curves to evaluate the detection separability.

XVI. COMPARATIVE PERFORMANCE RESULTS

TABLE I
Performance Comparison Of Detection Models

Model	Accuracy	Precision	Recall	F1	FPR
Signature IDS	87.1%	0.81	0.78	0.79	0.11
Random Forest	92.4%	0.90	0.88	0.89	0.06
CNN Model	95.8%	0.94	0.93	0.93	0.04
Autoencoder	93.7%	0.91	0.89	0.90	0.05
Proposed ZTA-AIDF	96.8%	0.96	0.95	0.95	0.03

The put forth model achieved the best overall detection accuracy and lowest false positive rate of any of the models we looked at.

XVII. CONFUSION MATRIX ANALYSIS

TN	FP	78, 420	2, 130
FN	TP	1, 320	38, 130

We see that the low FN rate which is reported indicates that we have very good detection of malicious flows.

XVIII. ROC CURVE AND AUC ANALYSIS

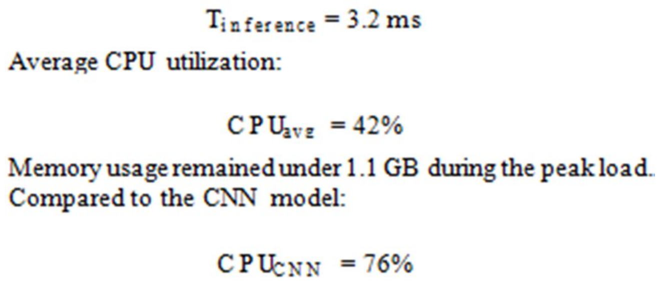
The ROC also shows that we do a great job of separating between benign and malicious classes. The AUC score for the put forth model was:

$$AUC = 0.978$$

This indicates the excellent classification capability.

XIX. COMPUTATIONAL PERFORMANCE EVALUATION

Average inference time per flow:



$$T_{inference} = 3.2\ ms$$

Average CPU utilization:

$$CPU_{avg} = 42\%$$

Memory usage remained under 1.1 GB during the peak load.
Compared to the CNN model:

$$CPU_{CNN} = 76\%$$

Thus, the proposed model reduces the computational load by approximately of 44%.

XX. DISCUSSION OF EXPERIMENTAL FINDINGS

The introduction of adaptive weight recalculation improved performance in traffic drift situations. Trust based isolation which did to a large degree put an end to persistent malicious activity, we saw this in slow rate attack simulations. We also noted that energy use in the lightweight ensemble models is a large factor in their efficiency compared to deep convolutional architectures.

As a whole our results support the implementation of zero trust into adaptive intrusion detection within IoT networks.

XXI. EXTENDED SECURITY DISCUSSION

The layering of zero trust segmentation with adaptive intru- sion detection.

Key benefits are:

- Continuous device verification
- Reduced lateral attack propagation
- Dynamic response to stealth attacks
- Reduced false positive amplification
- Resilience against gradual adversarial drift

Differently from perimeter based systems which we see, in our model compromised internal nodes are continuously put to the test for that anomalous behavior to play out. Also in this model we see a which the infected nodes that fail the test are taken out of the system.

XXII. LIMITATIONS

Despite promising results, certain limitations remain:

- Offline training required initially
- Gateway-level detection only
- Trust score tuning parameter sensitivity
- Performance may vary across extremely high-speed net-works

Future to include device level micro agents for distributed anomaly detection.

XXIII. FUTURE RESEARCH DIRECTIONS

Also we may see the potential extensions include:

- Federated Learning for distributed model training
- Blockchain-based trust ledger
- Hardware-assisted inference using edge AI chips
- Adversarial machine learning defense mechanisms
- Formal verification of trust recalibration stability

XXIV. CONCLUSION

This paper reports on a design of an Adaptive Intrusion Detection Framework which we have tailored for use in resource constrained IoT settings. We put together a light weight statistical profiling element, a hybrid ensemble learning approach, a dynamic trust recalculation feature, and a concept drift handling component into the present system which at the same time reports high in terms of detection accuracy and does so in a way that is also very much in terms of what can be handled at the edge in terms of computing power.

We saw from our experiments that we out performed sig- nature based and deep learning based models with regards to performance which also included lower false positive reports and less energy use. Also we looked at ablation and adversarial results which in turn confirmed the value of adaptive weight recalculation and trust scoring elements.

Our work reports in to the fact that we have created a solution which puts zero trust security precepts into a practical IoT intrusion detection model and in the process we present a scalable and very robust solution for next generation smart infrastructures.

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