Expert Knowledge Correlated Evaluation of Intrusion Detection System in Heterogeneous IoT

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Abstract—The dynamic heterogeneous IoT contexts adversely affect the performance of learning-based network intrusion detection and prevention systems resulting in increased misclassification rates—necessitating an expert knowledge correlated evaluation framework. The proposed framework includes intrusion root cause analysis and a correlation model that can be generalized over any network intrusion dataset, corresponding expert knowledge, detection technique, and learning-based algorithm. The experimentations prove the robustness of the propounded framework on imbalanced datasets.

Index Terms—Context awareness, correlated evaluation metrics, expert knowledge correlation, heterogeneous IoT, learning-based network intrusion detection and prevention, root cause analysis

I. INTRODUCTION

HETEROGENEOUS networks that offer ad hoc network-like flexibility and IoT network-like connectivity are suitable for ubiquitous computing and proliferating content consumption in critical applications across domestic and industrial space [1]–[3]. Such networks are called heterogeneous IoT (or HetIoT) [5].

Learning-based network intrusion detection systems (NIDS) for such HetIoT infrastructures suffer from high misclassification rates [1], [8] due to context-unaware statistical evaluation of (machine or deep) learning-based algorithms as HetIoT involves dynamic contexts. Such dynamic scenarios necessitate reinforcing an expert knowledge (EK) framework for context-aware decision-making and minimizing false alerts [2], [4], [6], [7] to avoid high recovery costs due to failure. EK can include information like high-level traffic behaviors, constituting device specifications, and operating conditions.

We propose a generalized EK correlated evaluation framework with correlated metrics that performs well on imbalanced data and can supplement any (machine or deep) learning-based algorithm to obtain reduced false alerts for any intrusion detection (ID) application, provided a relevant expert knowledgebase for the network traffic dataset is available. Furthermore, this framework permits policy distribution across

the HetIoT subnets for context-specific near real-time intrusion detection and prevention.

We evaluate our proposition on the SVM algorithm by employing the Bot-IoT dataset and constructing a relevant expert knowledge base with the following contributions:

- 1) A high-level EK framework (RCA table) for intrusion root cause analysis.
- 2) A reinforcement method (Correlation algorithm) for correlating ID alerts with EK inferences for reducing false alerts.
- 3) Correlated evaluation metrics derived from standard ID evaluation metrics based on the Correlation algorithm.

II. RELATED WORK

The existing NIDPS policies for heterogeneous networks [1], [3], [4] suffer from high misclassification rates due to context-unaware traffic processing by learning-based algorithms, adversely affecting the HetIoT performance.

Researchers have proposed means to reduce misclassifications involving threat context computation [4] and intrusion root cause analysis [8]. However, such works employ ontological techniques [7] that are computation-heavy [1] and provide no information on the decentralization of policies, affecting the real-time performance of HetIoT-NIDPS especially during big data processing.

III. CORRELATED EVALUATION FRAMEWORK

The dynamic contexts in a HetIoT adversely affect the context unaware low-level statistical inferences of ID algorithms. Thus, reinforcing them with the extracted high-level behavioral descriptions improves network redesign that is context-aware and resistant to frequent security compromises, benefitting from the interpretability of knowledge-driven specification and the adaptability of data-driven detection [1]. To achieve this, we propose an EK framework.

A. RCA Expert Knowledge Framework

The proposed RCA framework offers a high-level intuition for identifying faults in the HetIoT behavior for a threat context with potential attacks and analyzes root causes of the intrusions encountered. Such a setting is helpful for easier network maintenance, as it reduces examining the network logs. Moreover, interpreting network logs from heterogeneous devices is never straightforward and requires additional computations and time to normalize.

The framework contains the RCA table (Table I), offering a list of possible faults for an attack category compiled by

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domain experts, where an *attack* is associated with a high-level unexpected network *behavior*. In addition, the NID dataset [3] offers information about such behaviors—identified as specific *faults* and their probable *causes* that include system vulnerabilities. We use this information obtained from multiple repositories as the EK to correlate ID alerts.

B. Misuse Detection Model

Misuse detection classifies the network traffic instances according to the class labels.

Definition III.1 (Misuse Detection). *Let $D = \{d_t, y_t\}_{t=1}^M$ be the data-driven information (dataset). The prediction (binary classification) that an instance belongs to an attack class $C_i \in C$ where $C = \{0, 1\}$ is,*

$$P(f(d_t) = 1|C_i) \quad (1)$$

We employ the proposed Correlation model (Algorithm 1) to evaluate the *SVM* classifier alerts and obtain correlated alerts—resulting in *SVM-Corr* classifier. The Correlation algorithm is generic and is independent of learning-based algorithms, NID datasets and corresponding EK, and ID techniques.

C. Correlation Model

The Correlation model correlates the ID alerts with the EK inferences from the RCA table.

Definition III.2 (Correlation). *Let $E_{RCA}(k) \forall k \in K$ be an expert knowledge instance of a dataset instance $d \in D$. Let $\mathcal{E} : (d, k) \rightarrow C$ be an evaluation function such that, evaluating the dataset and the corresponding expert knowledge instances helps detect an attack label instance. i.e.,*

$$\mathcal{E}(d_q, k_r) = C_i \quad (2)$$

Therefore, the ID alerts and the corresponding EK inferences are correlated (i.e., yield same class labels) iff,

$$P(f(d_q)) \longleftrightarrow E_{RCA}(k_r) \quad (3)$$

1) *Correlation Algorithm*: Algorithm 1 offers the pseudocode for correlation—analogue to equation (3). Since E_{RCA} informs only about the attacks present in the system, it always checks for *TP* and *FN*. Thus, uncorrelated ID alerts lead to *FP*—analyzed and correctly classified as correlated *TN* (*CTN*) and *FN*—analyzed and correctly classified as correlated *TP* (*CTP*) through Algorithm 2, which is analogue to equation (2) and results in reduced false alerts.

The correlated alerts with labels and the EK inferences are updated to the knowledgebase (Fig. 1). Finally, the correlation algorithm outputs the alerts described in Table II.

2) *Correlated Intrusion Detection Metrics*: We formulate the correlated ID metrics from the results of Correlation algorithm. We derive the proposed metrics from the standard classification metrics of a learning-based algorithm.

The correlation error ξ due to inefficiency in preparing the RCA table E_{RCA} (i.e., unavailability of corresponding EK instance for an ID attack instance) results in missed

Algorithm 1: Correlation

Input: ID alerts, $P(f(d) = 1|C_i) - TP, FP, FN$;
Expert knowledge, $E_{RCA}(k)$
Output: Correlated misuse detection alerts with reduced false alarms – CTP, CTN

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1 procedure correlation( $P(f(d)), E_{RCA}(k)$ ):
2 Initialization:  $\{CTP, CTP_{count}\} \leftarrow 0$ 
3 for  $q = 1 \dots M$  do
4   for  $r = 1 \dots Q$  do
5     if  $P(f(d_q) = 1|C_i) \longleftrightarrow E_{RCA}(k_r)$  then
6       return  $CTP$ 
7        $CTP_{count} + = 1$ 
8     else
9        $compare\_EK(P(f(d_q)), y_i, E_{RCA}(k_r))$ 
10       $Update\ the\ knowledgebase$ 
11 return  $CTP_{count}$ 
12 end procedure
```

Algorithm 2: Compare Expert Knowledge

Input: ID alerts, $P(f(d) = 1|C_i) - TP, FP, FN$;
Ground truth, y ; Expert knowledge, $E_{RCA}(k)$
Output: Attack category and the corresponding high-level network fault

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1 procedure compare_EK( $P(f(d)), y, E_{RCA}(k)$ ):
2 Initialization:
    $\{CTP, CTN, CTP_{count}, CTN_{count}\} \leftarrow 0$ 
3 if  $P(f(d)) = 0$  and  $y = 1$  then
4   if  $y \longleftrightarrow ATTACK.E_{RCA}(k)$  then
5      $Identify\ FAULT\_ID.E_{RCA}(k),\ CAUSE.E_{RCA}(k)$ 
6     return  $CTN$ 
7      $CTN_{count} + = 1$ 
8   else
9     if  $y \longleftrightarrow ATTACK.E_{RCA}(k)$  then
10       $Identify\ FAULT\_ID.E_{RCA}(k),\ CAUSE.E_{RCA}(k)$ 
11      return  $CTP$ 
12       $CTP_{count} + = 1$ 
13 return  $CTP_{count}, CTN_{count}$ 
14 end procedure
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false ID alerts (*FN* and *FP*)—reducing the metric scores. Such misclassifications upon further examination lead to new HetIoT behaviors updated in the expert knowledgebase.

$$\xi = \xi_{FP} + \xi_{FN} \quad (4)$$

Therefore, we formulate the correlated ID evaluation metrics as follows:

- *Correlated Accuracy ($\mathcal{A}$):*

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

$$\Rightarrow \mathcal{A} = \frac{CTP + TN}{CTP + TN + CTN + \xi}$$

TABLE I
A SAMPLE OF ATTACK BEHAVIORS-WISE ROOT CAUSE ANALYSIS (RCA) FRAMEWORK
(REFER TO THE CONCLUSION SECTION FOR THE DETAILED VERSION)

Attack	Behavior	Fault	Fault ID	Cause
DoS	Large incoming network traffic from a HetIoT client to a server IP, Disrupted services	Apache web server receiving client requests with many HTTP headers (around 10,000), Server load average ≥ 5 or more, Out of memory HTTPD daemon (apache2)	D1	Legitimate HTTP request headers ≤ 20
Recon	Large incoming network traffic across multiple HetIoT clients from single or multiple external IPs within a specific time window	ICMP echo requests (ip-sweep)	R1	Device replying before a threshold of requests exposes its IP
...	...	...	...	...

Fig. 1. Proposed correlated NIDS architecture

TABLE II
STANDARD ID ALERTS AND THEIR CORRESPONDING CORRELATIONS

Classification Alerts	Correlated Alerts
True Positive (TP)	Correlated True Positive (CTP)
True Negative (TN)	-
False Positive (FP)	Correlated True Negative (CTN)
False Negative (FN)	Correlated True Positive (CTP)

- *Correlated Precision (P)*:

$$\begin{aligned} Precision &= \frac{TP}{TP + FP} \\ &\Rightarrow \mathcal{P} = \frac{CTP}{CTP + CTN + \xi_{FP}} \end{aligned} \quad (6)$$

- *Correlated Recall (R)*:

$$\begin{aligned} Recall &= \frac{TP}{TP + FN} \\ &\Rightarrow \mathcal{R} = \frac{CTP}{CTP + \xi_{FN}} \end{aligned} \quad (7)$$

- *Correlated F1-score (F)*:

$$\begin{aligned} F1 - score &= 2 \times \frac{Precision \times Recall}{Precision + Recall} \\ &\Rightarrow \mathcal{F} = 2 \times \frac{\mathcal{P} \times \mathcal{R}}{\mathcal{P} + \mathcal{R}} \end{aligned} \quad (8)$$

IV. ALGORITHM ANALYSIS

We perform formal analyses¹ of the Correlation algorithm to explore its properties and prove that it can offer near real-time performance.

¹Refer to the Conclusion section for proofs.

Theorem IV.1 (Time Complexity of Correlation Algorithm). *The worst-case time complexity of the Correlation algorithm is $\mathcal{T}_{correlation} \rightarrow \mathcal{O}(MQ)$.*

Corollary IV.1.1 (Average Correlations). *The average correlations of the Correlation algorithm linearly reduce to $\mathcal{T}_{correlation} \rightarrow \mathcal{O}(M)$.*

Definition IV.1 (Generalizability of Correlation Model). *Since the Correlation model utilizes context-specific expert knowledge from a network traffic data of any attack type, it can supplement any (machine or deep) learning-based algorithm for supervised misuse detection or unsupervised anomaly detection, provided a suitable expert knowledgebase is available.*

Hence, the proposed algorithm can adapt to any intrusion detection technique and detection algorithm, independent of network traffic and expert knowledge data.

Thus, we say that the Correlation model is generalized over network traffic dataset $\mathcal{D}$, expert knowledge $\mathcal{E}$, intrusion detection technique $\mathcal{ID}$, and detection algorithm $\mathcal{A}$. Therefore,

$$Correlation : \mathcal{G}(\mathcal{D}, \mathcal{E}, \mathcal{ID}, \mathcal{A}) \quad (9)$$

V. EXPERIMENTAL ANALYSIS AND DISCUSSION

We begin by preparing the dataset for classification, then perform misuse detection using the SVM algorithm. We then correlate the misclassified alerts from SVM through the Correlation algorithm (SVM-Corr classifier) to obtain the correlated results with minimized false alerts.

Finally, we perform binary classification with SVM-Corr by splitting the dataset into *Normal* and four attack classes (*DoS*, *DDoS*, *Recon*, and *Theft*). We choose this setting to distribute the attack-wise trained classifier models across the HetIoT according to each subnet's specific threat (attack) contexts.

The experimental setup is according to the specifications in the *scikit-learn*² machine learning library.

A. Experimental Environment

We list the experimental settings—including the hardware specifications and the algorithmic parameters used for the work in Table III.

²<https://scikit-learn.org/stable/>

TABLE III
EXPERIMENTAL ENVIRONMENT SETTINGS FOR MISUSE DETECTION

Parameter	Specification
CPU	AMD with 6 cores (3.0 GHz)
RAM	24 GB (3200 MHz)
Detection algorithms	SVM, SVM-Corr
SVM settings	LinearSVC, CV = 4, max_iter = 100,000

B. Dataset Preprocessing

We preprocess the 10-best features CSV file of the Bot-IoT dataset using the Label and One-hot encoding techniques to convert all the categorical features (like protocol, ip address, port, and class label) into numerals for two types of binary classification:

- Normal vs. Attack
- Normal vs. {DoS, DDoS, Reconnaissance, Theft}

1) *Dataset Normalization*: We scale the encoded dataset features for classification. First, the technique standardizes the feature instances by removing the mean and scaling them to unit variance, as required by the SVM algorithm.

C. Results and Analysis

We present the details of the experiments conducted and the results obtained, supporting our claims in previous sections.

1) *SVM-Corr Classifier*: The SVM-Corr classifier makes better predictions with lower false alarm rates, improving classification performance.

We experiment to evaluate the proposed approach's performance compared to the existing work [3] by setting up the *Linear SVM* classifier with 4-fold cross-validation and max iterations set to 100,000 (for convergence). However, in both cases, the classifier suffered from longer training times (in the order of 10^3 seconds). Table IV presents the results.

TABLE IV
SVM AND SVM-CORR CLASSIFIER PERFORMANCES (IN %) ON THE COMPLETE DATASET (NORMAL VS. ATTACK WITH CV=4)

Classifier	Metric	Result (%)
SVM-Corr	$\mathcal{A}$	99.9951
SVM	Accuracy	88.3727
SVM-Corr	$\mathcal{P}$	99.9974
SVM	Precision	100
SVM-Corr	$\mathcal{R}$	99.9740
SVM	Recall	88.3712

We split the Bot-IoT dataset based on the existing attack types and present the corresponding class-wise (Normal and 4 Attacks) distribution in Table V.

Table VI presents the comparative performances of the SVM and SVM-Corr classifiers on the class-wise distributed imbalanced dataset—indicating improved performance.

VI. CONCLUSION

We present an RCA EK correlated NIDS evaluation framework generalizable across multiple NID techniques, algorithms, datasets, and corresponding EK. Furthermore, this

TABLE V
CLASS-WISE BOT-IOT TRAFFIC SAMPLES DISTRIBUTION

Class	Train set	Test set
Normal	370	107
DoS	1320148	330112
DDoS	1541315	385309
Reconnaissance	72919	18163
Theft	65	14

TABLE VI
ATTACK-WISE SVM AND SVM-CORR CLASSIFIER PERFORMANCES (IN %) ON THE NORMALLY DISTRIBUTED IMBALANCED BOT-IOT DATASET

Classifier	Attack	Accuracy	Precision	Recall	F1-score
SVM	DoS	99.9821	99.9879	99.9942	99.9911
	DDoS	97.8755	99.9920	97.8829	98.9262
	Recon	98.4925	99.9832	98.5089	99.2405
	Theft	19.7917	100	19.7917	33.0435
		$\mathcal{A}$	$\mathcal{P}$	$\mathcal{R}$	$\mathcal{F}$
SVM-Corr	DoS	99.9985	99.9994	99.9376	99.9997
	DDoS	99.9979	99.9997	99.8104	99.9998
	Recon	99.9834	99.9945	100	99.9972
	Theft	100	100	100	100

framework results in near real-time performance and improved efficiency on imbalanced datasets.

In our future work, we attempt to qualify the impact of attack alerts in a HetIoT threat context by defining a *Fault Score* metric for the RCA table for alert prioritization and threat (attack) severity assessment.

Link for the supplementary information (with the detailed *RCA table* and *algorithm analyses*):

<https://drive.google.com/drive/folders/1gZ5WobZlApszoxq83iFhN71GqgBMVKL?usp=sharing>

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