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Expert Knowledge Correlated Intrusion Detection System Evaluation Framework for Heterogeneous IoT

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Abstract

The dynamic contexts of heterogeneous Internet of Things (HetIoT) adversely affect the performance of learning-based network intrusion detection systems (NIDS) resulting in increased misclassification rates—necessitating an expert knowledge correlated evaluation framework. The proposed generalizable framework includes intrusion root cause analysis, correlation model, and correlated classification metrics that can be generalized over any NID dataset, corresponding expert knowledge, detection technique, and learning-based algorithm to facilitate context-awareness in reducing false alerts. To achieve this, we perform experiments on the Bot-IoT dataset—with generalized traffic behaviors from multiple existing NID datasets—employing the Support Vector Machine (SVM) machine learning and Multilayer Perceptron (MLP) shallow neural network classifiers, demonstrating the generalizability,

robustness, and improved performance of the propounded framework compared to the existing literature. Furthermore, the proposed framework offers minimal processing overhead on the classifier algorithms.

Keywords: Context-awareness, Correlated evaluation metrics, Expert knowledge correlation, Heterogeneous IoT, Network intrusion detection framework, Root cause analysis

1 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]–[9]. Such networks are called heterogeneous IoT (or HetIoT) [13].

Learning-based network intrusion detection systems (NIDS) for such HetIoT infrastructures suffer from high misclassification rates due to context-unaware statistical evaluation of (machine or deep) learning-based algorithms as HetIoT involves dynamic contexts [1], [25]. Such dynamic scenarios necessitate reinforcing an expert knowledge (EK) framework for context-aware decision-making and minimizing false alerts [5], [11], [15], [16] to avoid high recovery costs due to failure. EK can include information like high-level traffic behaviors, constituting device specifications, operating conditions, and human feedback.

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. The generalizability of the propounded framework is achieved by performing classification on the Bot-IoT dataset [9], which contains the traffic characteristics of IoT devices in addition to those from the existing NID datasets. Furthermore, this framework permits policy distribution across the HetIoT subnets for context-specific intrusion detection and prevention.

We evaluate our proposition on the SVM and MLP classifier algorithms by employing the Bot-IoT dataset [9] and constructing a relevant expert knowledgebase with the following contributions required for a generalized heterogeneous NIDS framework:

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.

Table 1 Notations used in the paper and their description

Notation	Description
$D_{M \times N} = \{d_t, y_t\}$	Network traffic dataset having M samples and N features with class labels
$\mathbf{P}(f(d))$	Misuse detection prediction
$C_i \in C$	$C_i = \{0, 1\}$ binary class labels
$E_{RCA}(k)$	k^{th} RCA expert knowledge instance
$\mathcal{E}(d_q, k_r)$	Evaluation function
ξ, ξ_{FP}, ξ_{FN}	RCA EK error, FP error, FN error
$\mathcal{A}, \mathcal{P}, \mathcal{R}, \mathcal{F}$	Correlated classification metrics – Accuracy, Precision, Recall, and F1-score
$\mathcal{T}$	Time complexity
$\mathbb{F} : \mathcal{G}(\mathcal{D}, \mathcal{E}, \text{ID}, \mathcal{A})$	NIDS function generalized over NID dataset, EK, ID technique, and algorithm

- Extensive experimentations on the Bot-IoT dataset generalized traffic behaviors using SVM and NLP classifiers—demonstrating the context-awareness, robustness and generalizability of the propounded HetIoT-NIDS framework.

Table 1 provides a list of symbols used in the paper and their description.

2 Related Work

The existing NIDS policies for heterogeneous networks [1], [6]-[12] 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 [11] and intrusion root cause analysis [25]. However, such works employ ontological techniques [16] that are computation-heavy [1] and provide no information on the decentralization of policies, affecting the context-awareness of HetIoT-NIDS especially during big-data processing.

We present a comparative summary of the existing heterogeneous NIDS schemes in Table 2 with respect to the proposed decentralization (*Dec*), heterogeneity (*Het*), context-awareness (*CA*), and generalizability (*G*) parameters.

3 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.

Table 2 Comparative summary of existing heterogeneous NIDS schemes with the proposed framework parameters

Scheme	<i>Dec</i>	<i>Het</i>	<i>CA</i>	<i>G</i>
[2]	✗	✓	✗	D
[3]	✗	✓	✓	D, A
[4]	✗	✓	✗	D
[5]	✗	✓	✗	D
[6]	✓	✓	✗	D
[7]	✗	✗	✗	D, A
[8]	✗	✓	✗	D, E, A
[9]	✗	✓	✗	D, A
[10]	✓	✗	✗	D, ID, A
[11]	✗	✓	✓	-
[12]	✗	✓	✗	D, ID, A
[16]	✓	✓	✓	-
Proposed work	✓	✓	✓	D, E, ID, A

3.1 Root Cause Analysis Expert Knowledge Framework

The proposed root cause analysis expert knowledge (RCA EK) 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 frequently examining network logs. Moreover, interpreting network logs from heterogeneous devices is never straightforward and requires additional computations and time to normalize the metadata information from various sources.

Table 3 presents a sample of the proposed attack-wise RCA expert knowledgebase. The detailed version is presented in the Appendix section.

3.2 Misuse Detection Model

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

Definition 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,*

$$\mathbf{P}(f(d_t) = 1 \mid C_i) \quad (1)$$

We employ the proposed misuse detection model using the SVM and MLP classifiers.

Table 3 Attack-wise RCA EK framework sample (refer to Appendix A 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 client requests with many HTTP headers (around 10,000), Server load average ≥ 5 , Out of memory HTTPD daemon (apache2)	D1	Legitimate HTTP request headers ≤ 20
DDoS	Large incoming network traffic from multiple HetIoT clients to a server IP with all IoT devices following specific traffic pattern, Closely grouped and coordinated behavior of bots, Communication with large number of devices, and Varying destination IPs between time windows	Testing specific credentials in specific ports, Downloading specific type of binary code, Exchanging keep-alive messages, Attacks with specific structures, Generating attack traffic with very few random elements, Infecting through TCP (23-2323, 7547) ports, Larger TCP traffic share, Smaller packet sizes and very small inter-packet interval (mirai)	DD1	Unsecure remote router access from ISP through port 7547, Webcam vulnerabilities allowing access through port 81, UPnP vulnerability in client router, and Webcam zero-day vulnerability allowing password file access
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
Theft	Stealthy approach to evade detection, Constantly monitoring and interacting with compromised systems, Appearing similar to legitimate traffic	Advanced social engineering techniques, Obfuscated malwares, Backdoor communication with remote C&C via TCP port 443 (injection flaw)	T1	Encrypted traffic – difficult to inspect, Zero-day vulnerability in the Internet Explorer browser

3.3 Correlation Model

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

Definition 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,

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

3.3.1 Correlation Algorithm

We employ the proposed Correlation model in Algorithms 1 and 2 to correlate the predicted alerts obtained from the learning-based classifiers. Algorithm 1—analogue to equation (3) depends on the Algorithm 2, which is analogue to equation (2). The Correlation algorithm is generic and is independent of learning-based algorithms, NID datasets and corresponding EK, and ID techniques.

Algorithm 1 Correlation

Require: ID alerts, $\mathbf{P}(f(d) = 1 \mid C_i) - TP, FP, FN$; Expert knowledge, $E_{RCA}(k)$

Ensure: Correlated misuse detection alerts with reduced false alarms – CTP, CTN

```

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

```

Algorithm 2 Compare Expert Knowledge

Require: ID alerts, $\mathbf{P}(f(d) = 1 \mid C_i) - TP, FP, FN$; Ground truth, y ; Expert knowledge, $E_{RCA}(k)$

Ensure: Attack category and the corresponding high-level network fault

- 1: **procedure** *compare_EK*($\mathbf{P}(f(d)), y, E_{RCA}(k)$):
- 2: **Initialization:** $\{CTP, CTN, CTP_{count}, CTN_{count}\} \leftarrow 0$
- 3: **if** $\mathbf{P}(f(d)) = 0$ **and** $y = 1$ **then**
- 4: **if** $y \longleftrightarrow \text{ATTACK}.E_{RCA}(k)$ **then**
- 5: Identify: $\text{Fault}.E_{RCA}(k), \text{Fault_ID}.E_{RCA}(k), \text{Cause}.E_{RCA}(k)$
- 6: **return** CTN
- 7: $CTN_{count} + = 1$
- 8: **end if**
- 9: **else**
- 10: **if** $y \longleftrightarrow \text{ATTACK}.E_{RCA}(k)$ **then**
- 11: Identify: $\text{Fault}.E_{RCA}(k), \text{Fault_ID}.E_{RCA}(k), \text{Cause}.E_{RCA}(k)$
- 12: **return** CTP
- 13: $CTP_{count} + = 1$
- 14: **end if**
- 15: **end if**
- 16: **return** CTP_{count}, CTN_{count}
- 17: **end procedure**

Fig. 1 Proposed correlated HetIoT-NIDS architecture

The correlated alerts with labels and the EK inferences are updated to the knowledgebase—as in Fig. 1. Finally, the Correlation algorithm outputs the alerts described in Table 4.

3.3.2 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)

Table 4 Standard ID alerts and their 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)

results in missed false ID alerts (FN and FP)—reducing the metric scores.

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

Such misclassifications upon further examination lead to new HetIoT behaviors updated in the expert knowledgebase, gradually reducing the error. i.e.,

$$\begin{aligned} (\xi_{FP}, \xi_{FN}) &\downarrow 0 \\ \Rightarrow \xi &\downarrow 0 \end{aligned} \quad (5)$$

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

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

$$\begin{aligned} Accuracy &= \frac{TP + TN}{TP + TN + FP + FN} \\ \Rightarrow \mathcal{A} &= \frac{CTP + TN}{CTP + TN + CTN + \xi} \end{aligned} \quad (6)$$

- *Correlated Precision* ($\mathcal{P}$):

$$\begin{aligned} Precision &= \frac{TP}{TP + FP} \\ \Rightarrow \mathcal{P} &= \frac{CTP}{CTP + CTN + \xi_{FP}} \end{aligned} \quad (7)$$

- *Correlated Recall* ($\mathcal{R}$):

$$\begin{aligned} Recall &= \frac{TP}{TP + FN} \\ \Rightarrow \mathcal{R} &= \frac{CTP}{CTP + \xi_{FN}} \end{aligned} \quad (8)$$

- *Correlated F1-score* ($\mathcal{F}$):

$$\begin{aligned} F1 - score &= 2 \times \frac{Precision \times Recall}{Precision + Recall} \\ \Rightarrow \mathcal{F} &= 2 \times \frac{\mathcal{P} \times \mathcal{R}}{\mathcal{P} + \mathcal{R}} \end{aligned} \quad (9)$$

4 Algorithm Analysis

We perform formal analyses of the Correlation algorithm to explore its properties and prove that it has a lower computational overhead.

Theorem 1 (Time Complexity of Correlation Algorithm). *For M traffic instances and Q expert knowledge instances, the worst-case time complexity of the Correlation algorithm is*

$$\mathcal{T}_{correlation} \rightarrow \mathcal{O}(MQ)$$

Proof The proposed correlation framework constitutes the *correlation* and *compare_EK* procedures in Algorithms 1 and 2, respectively.

Algorithm 2 begins with an **initialization** instruction I_1 (in *line 2*) with constant time, followed by a conditional instruction (either **if** I_2 in *line 3* or **else** I_3 in *line 9*) with a total of *two* instructions. *Four* additional instructions $I_{21} - I_{24}$ (in *lines 4 - 7*) follow I_2 , each with constant time. Similarly *four* instructions $I_{31} - I_{34}$ (in *lines 10 - 13*) follow I_3 . Finally, a **return** instruction I_4 (in *line 16*) is executed in constant time. Therefore, the time complexity of Algorithm 2 is as follows:

$$I_{compare_EK} \leftarrow \begin{cases} I_1 + I_2 + I_{21} + I_{22} + I_{23} + I_{24} + I_4 \\ I_1 + I_3 + I_{31} + I_{32} + I_{33} + I_{34} + I_4 \end{cases} \quad (10)$$

Any one of the above paths is executed with a total of *seven* instructions in constant time.

Algorithm 1 correlates ID alerts with corresponding EK inferences for a matched attack category in each instance. It begins with an **initialization** instruction I_1 (in *line 2*) with constant time, followed by a conditional instruction (either **if** I_2 in *line 5* or **else** I_3 in *line 8*), totaling *two* instructions executing MQ times. I_2 is followed by *two* more instructions I_{21} and I_{22} (in *lines 6 and 7*) with constant times and I_3 is followed by a **function call** to Algorithm 2 with $I_{compare_EK}$ time and an **update** instruction I_{31} (in *lines 9 and 10*), totaling *nine* instructions with constant time. Therefore, the time complexity of the Correlation algorithm is as follows:

$$I_{correlation} \leftarrow \begin{cases} I_1 + MQ \times (I_2 + I_{21} + I_{22}) \\ I_1 + MQ \times (I_3 + I_{compare_EK} + I_{31}) \end{cases} \quad (11)$$

The above execution paths contain $1 + 3 \times MQ$ and $1 + 9 \times MQ$ instructions, respectively.

Hence, it is clear from the above equations that the worst-case time complexity of the Correlation algorithm involves executing $1 + 9 \times MQ$ instructions at most. Therefore, the time complexity of the proposed Correlation algorithm is,

$$\mathcal{T}_{\text{correlation}} \rightarrow \mathcal{O}(MQ) \quad (12)$$

□

Corollary 1 (Average Correlations). *The average correlations of the Correlation algorithm linearly reduce to*

$$\mathcal{T}_{\text{correlation}} \rightarrow \mathcal{O}(M)$$

Proof Let $D = \{d_i, y_i\}_{i=1}^M \in \mathbb{R}^{M \times N}$ be the network traffic dataset and $E_{RCA} = \{k_j, y_j\}_{j=1}^Q \in \mathbb{R}^{Q \times 5}$ be the corresponding expert knowledgebase for a matching attack category C .

For a sufficiently large network traffic dataset, the corresponding expert knowledgebase is comparatively very small—as a large number of the dataset instances refer to a very small set of EK instances with a matching attack category in a threat context. Hence, we have

$$D_{(M \times N)} \gg E_{RCA_{(Q \times 5)}} \quad (13)$$

because $\mathbb{R}^{Q \times 5} \ll \mathbb{R}^{M \times N}$. Hence Q becomes negligible against M on an average.

Therefore, the average-case time complexity of the Correlation algorithm is

$$\mathcal{T}_{\text{correlation}} \rightarrow \mathcal{O}(M) \quad (14)$$

□

We introduce the *Generalizability* property as a part of the proposed evaluation framework.

Definition 3 (Generalizability). *Let $\mathbb{F}$ be an NIDS function accommodating a dataset D , corresponding expert knowledgebase E , intrusion detection technique ID , and corresponding algorithm A . The Generalizability of $\mathbb{F}$ is*

$$\mathbb{F} : \mathcal{G}(D, E, ID, A) \quad (15)$$

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 Correlation algorithm can adapt to any NID technique and detection algorithm, independent of network traffic and EK data.

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

$$\text{Correlation} : \mathcal{G}(D, E, ID, A) \quad (16)$$

Similarly, the proposed Correlated ID metrics work with the predictions of any NID technique and detection algorithm of any dataset and the corresponding EK. Therefore,

$$\text{Correlated ID Metrics} : \mathcal{G}(\mathcal{D}, \mathcal{E}, \text{ID}, \mathcal{A}) \quad (17)$$

5 Experimental Analysis and Discussion

Firstly, we prepare the dataset for classification, then perform misuse detection using the SVM classifier algorithm on the complete dataset. We then correlate the misclassified alerts from SVM through the Correlation algorithm (SVM-Corr) in comparison with [9] to obtain the correlated results with minimized false alerts.

Secondly, we perform comparative binary and multiclass classifications with SVM and SVM-Corr machine learning and MLP and MLP-Corr shallow neural network algorithms 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*¹ machine learning library.

5.1 Experimental Environment

We list the experimental settings—including the hardware specifications and the algorithmic parameters used for the work in Table 5.

Table 5 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	<code>LinearSVC; cv=4; max_iter=100,000</code>
MLP settings	<code>solver=sgd; activation=relu;</code> <code>alpha=0.0001; random_state=1;</code> <code>hidden_layer_sizes=(5,2)</code>

5.2 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:

¹<https://scikit-learn.org/stable/>

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

5.2.1 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.

5.3 Results and Analysis

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

5.3.1 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 [9] 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 6 presents the results.

Table 6 SVM and SVM-Corr classifier performances (in %) on the complete dataset (Normal vs. Attack with CV=4)

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

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 7.

Table 7 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 8 presents the comparative performances of the SVM and SVM-Corr classifiers on the attack-wise distributed imbalanced dataset—indicating improved performance. The poor performance of SVM on the Theft attack set is due to very small number of available samples, causing the classifier to not generalize efficiently. The attack-wise training times of SVM and SVM-Corr are of the same order for DoS, DDoS, and Recon attacks—supporting the hypothesis in Corollary 1 and significantly increases for Theft samples—as hypothesized in Theorem 1.

The corresponding confusion matrices in Table 9 indicate the bias of Normal distribution towards class with majority samples, resulting in higher false positives for DoS, DDoS, and Recon and higher false negatives for Theft samples (in red) and the resulting inconsistencies (in blue) despite having good performance scores. However, by incorporating the proposed Correlation model, the SVM performs consistently better with reduced false alerts.

Table 8 Attack-wise SVM and SVM-Corr classifier performances (in %) on the imbalanced dataset from Table 7 with training time (in seconds)

Classifier	Attack	Accuracy	Precision	Recall	F1-score	Training Time
SVM	DoS	99.9821	99.9879	99.9942	99.9911	27.009
	DDoS	97.8755	99.9920	97.8829	98.9262	107.723
	Recon	98.4925	99.9832	98.5089	99.2405	2.277
	Theft	19.7917	100	19.7917	33.0435	0.012
		$\mathcal{A}$	$\mathcal{P}$	$\mathcal{R}$	$\mathcal{F}$	
SVM-Corr	DoS	99.9985	99.9994	99.9376	99.9997	28.608
	DDoS	99.9979	99.9997	99.8104	99.9998	110.704
	Recon	99.9834	99.9945	100	99.9972	2.924
	Theft	100	100	100	100	0.334

Table 9 Attack-wise binary confusion matrices of SVM and SVM-Corr classifiers from Table 8

Classifier	Attack	TN	FP	FN	TP
SVM	DoS	0.05	0.95	0.0	1.0
	DDoS	0.03	0.97	0.02	0.98
	Recon	0.0	1.0	0.01	0.99
	Theft	0.0	0.0	0.8	0.2
		CTN	FP	FN	CTP
SVM-Corr	DoS	0.95	0.05	0.01	0.99
	DDoS	0.99	0.01	0.01	0.99
	Recon	0.98	0.02	0.01	0.99
	Theft	1.0	0.0	0.0	1.0

Table 10 presents the multiclass classification confusion matrices of SVM and SVM-Corr classifiers. We observe the effect of imbalance in the performance scores of Normal and Theft instances by SVM and the improvement offered by the proposed Correlation algorithm in SVM-Corr.

Table 10 Attack-wise multiclass confusion matrices of SVM and SVM-Corr classifiers

			Prediction				
			Normal	DoS	DDoS	Recon	Theft
SVM	Truth	Normal	0.41	0.2	0.3	0.06	0.03
		DoS	0.0	0.99	0.01	0.0	0.0
		DDoS	0.0	0.01	0.99	0.0	0.0
		Recon	0.01	0.03	0.03	0.93	0.0
		Theft	0.0	0.24	0.54	0.0	0.22
			Normal	DoS	DDoS	Recon	Theft
SVM-Corr	Truth	Normal	0.97	0.01	0.02	0.0	0.0
		DoS	0.0	0.99	0.01	0.0	0.0
		DDoS	0.0	0.01	0.99	0.0	0.0
		Recon	0.0	0.0	0.0	1.0	0.0
		Theft	0.0	0.0	0.0	0.0	1.0

5.3.2 MLP-Corr Classifier

We choose a shallow neural network classifier to demonstrate the generalizability of the proposed RCA EK framework. We compare the binary classification performances of MLP and MLP-Corr algorithms in Table 11 and present the corresponding confusion matrices in Table 12, observing similar behaviors for SVM and MLP algorithms.

Table 11 Attack-wise MLP and MLP-Corr classifier performances (in %) on the imbalanced dataset from Table 7 with training time (in seconds)

Classifier	Attack	Accuracy	Precision	Recall	F1-score	Training Time
MLP	DoS	99.9873	99.9873	100	99.9936	41.433
	DDoS	99.9818	99.9857	99.9961	99.9909	50.847
	Recon	98.5864	99.9832	98.6028	99.2882	7.597
	Theft	11.4583	100	11.4583	20.5607	0.233
		$\mathcal{A}$	$\mathcal{P}$	$\mathcal{R}$	$\mathcal{F}$	
MLP-Corr	DoS	99.9956	99.9974	99.9437	99.9988	43.138
	DDoS	99.9979	99.9993	99.7648	99.9934	53.055
	Recon	99.8990	99.9945	100	99.9792	8.304
	Theft	100	100	100	100	0.46

Table 12 Attack-wise confusion matrices of MLP and MLP-Corr classifiers from Table 10

Classifier	Attack	TN	FP	FN	TP
MLP	DoS	0.0	1.0	0.0	1.0
	DDoS	0.11	0.89	0.0	1.0
	Recon	0.0	1.0	0.01	0.99
	Theft	0.0	0.0	0.89	0.11
		CTN	FP	FN	CTP
MLP-Corr	DoS	0.97	0.03	0.01	0.99
	DDoS	0.99	0.01	0.02	0.98
	Recon	0.98	0.02	0.02	0.98
	Theft	1.0	0.0	0.0	1.0

The MLP and MLP-Corr multiclass classification confusion matrices in Table 13 demonstrates similar behavior as SVM and SVM-Corr.

Table 13 Attack-wise multiclass confusion matrices of MLP and MLP-Corr classifiers

		Prediction					
		Normal	DoS	DDoS	Recon	Theft	
MLP	Truth	Normal	0.32	0.25	0.34	0.05	0.04
		DoS	0.0	0.99	0.01	0.0	0.0
		DDoS	0.0	0.01	0.99	0.0	0.0
		Recon	0.02	0.05	0.06	0.87	0.0
		Theft	0.0	0.28	0.6	0.0	0.12
		Normal	DoS	DDoS	Recon	Theft	
MLP-Corr	Truth	Normal	0.98	0.01	0.01	0.0	0.0
		DoS	0.0	0.99	0.01	0.0	0.0
		DDoS	0.0	0.01	0.99	0.0	0.0
		Recon	0.0	0.0	0.0	1.0	0.0
		Theft	0.0	0.0	0.0	0.0	1.0

Finally, we provide a comparative analysis of the proposed work with the existing NIDS schemes in Table 14. The proposed techniques perform better compared to the existing ones upon considering the attack-wise performance scores and training times together.

5.4 Observations

We provide few instances connecting the key information from the RCA EK with the misclassified misuse detection alerts, as demonstrated in Algorithm 2. Similarly, we correlate the EK for all the other misclassifications.

Table 14 Comparative results of existing schemes on the dataset distribution from Table 7

Scheme	Classifier	Attack	Accuracy	Precision	Recall	F1-score	Training Time (seconds)		
[6]	Logistic Regression	Four attacks	80.9	80.4	88.9	84.4	3.222		
	Naive Bayes		45.6	88.4	7.6	14.0	0.360		
	k Nearest Neighbors		99.8	99.8	99.8	99.8	2.290		
	Decision Tree		100	100	100	100	8.110		
	AdaBoost		100	100	100	100	176.240		
	Random Forest		100	100	100	100	59.320		
	Radial Basis SVM		100	100	100	100	518,400.540		
	Linear SVM		100	100	100	100	451,215.210		
	[8]		Bayes Net	Four attacks	99.77	100	99	99.5	29.26
			C4.5		99.99	100	100	100	17.1
Naive Bayes		99.79	99		98	99.5	4.03		
Random Forest		99.99	100		100	100	198.83		
Random Tree		99.99	100		100	100	4.32		
[12]	Feed forward Neural Network	Four attacks	95.0	95.0	95.0	95.0	—		
	Self-normalizing Neural Network		91.0	92.0	91.0	91.0			
Proposed Work	SVM-Corr	DoS	99.9985	99.9994	99.9376	99.9997	28.608		
		DDoS	99.9979	99.9997	99.8104	99.9998	110.704		
		Recon	99.9834	99.9945	100	99.9972	2.924		
		Theft	100	100	100	100	0.334		
	MLP-Corr	DoS	99.9956	99.9974	99.9437	99.9988	43.138		
		DDoS	99.9979	99.9993	99.7648	99.9934	53.055		
		Recon	99.8990	99.9945	100	99.9792	8.304		
		Theft	100	100	100	100	0.46		

- The traffic instance “2071” in the *DoS Test* dataset turned out to be a misclassification. The high-level DoS behavior implies that the destination IP receives a large volume of traffic, characterized by the “N_IN_Conn_P_DstIP” feature in the dataset. However, the feature had a very low value, which indicates that it is a *false positive*.
- The misclassified traffic instance “2” in the Theft Test dataset is a false negative. The corresponding high-level expert knowledge hints that the traffic pattern for information theft closely resembles the Normal traffic, necessitating traffic analysis—resulting in Theft.

We make the following observations from the above information:

- The EK framework minimizes log file analysis.
- Since the size of the EK entries are much lower than the dataset size, it facilitates near real-time operation, as demonstrated in the algorithm analysis.

6 Conclusion

We present an RCA EK correlated NIDS evaluation framework generalizable across multiple NID techniques, algorithms, datasets, and corresponding EK. Furthermore, this framework results in training times closer to the SVM and MLP algorithms with minimal computational overhead. It also provides improved classification scores on imbalanced datasets due to context-awareness.

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. Furthermore, we investigate the bias of Normal distribution and propose a class imbalance invariant data preprocessing technique, which is necessary for online (real-time) threat assessment with smaller number of network traffic samples. We also intend to experiment on different attacks from multiple datasets.

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Declarations

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Conflicts of interest/Competing interests

The authors declare that they have no conflict of interest.

Availability of data and material

The additional data required for the proposed work is presented in Appendix A.

Code availability

Custom code

Authors' contributions

Conceptualization, S.P.S.P. and N.A.; methodology, N.A. and S.P.S.P.; software, N.A. and S.P.S.P.; validation, N.A., S.P.S.P. and H.J.; formal analysis N.A. and S.P.S.P.; investigation, N.A., S.P.S.P. and H.J.; resources, N.A., S.P.S.P. and H.J.; data curation, N.A. and S.P.S.P.; writing – original draft preparation, N.A. and S.P.S.P.; writing – review and editing, N.A., S.P.S.P., H.J., and K.K.; visualization, K.K. and S.P.S.P.; supervision, K.K., H.J., and S.P.S.P.; project administration, K.K. and H.J.

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Appendix A Expert Knowledgebase

In this section, we provide the detailed version of the RCA expert knowledgebase, (E_{RCA}) divided attack-wise. The setting presented, reduces search time based on the attack type—resulting in lower training time.

The framework contains the RCA EK of the Bot-IoT dataset [9] in Tables A1 through A4, offering a list of possible faults for an attack category compiled by domain experts, where an *attack* is associated with a high-level unexpected network *behavior*. We extract the information from the resources [14]-[24] mentioned in [9]. In addition, the Bot-IoT NID dataset 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.

Table A1 RCA EK framework for Denial of Service (DoS)

Attack	Behavior	Fault	Fault ID	Cause
DoS	Large incoming network traffic from a HetIoT client to a server IP, Disrupted services	Apache web server client requests with many HTTP headers (around 10,000), Server load average ≥ 5 , Out of memory HTTPD daemon (apache2)	D1	Legitimate HTTP request headers ≤ 20
		URL requests with frontslashes $>$ threshold (back)	D2	Victim HTTPD process consuming excess CPU time
	Flooding email server with messages, Large number of mail messages from or to a user within a short time (mailbomb)	Spoofed SYN packet, same source and destination IP, TCP-SYN packet through TCP sockets interface (land)	D3	IP packets with same source and destination addresses are not allowed
		Half-open TCP connections add records to the TCPD server with pending connections, Simultaneous SYN packets from an unreachable host targeted to a machine (neptune)	D4	Varied message thresholds on each site
	Receiving oversized IP packets, Systems crashing, freezing, and rebooting, Noting ICMP packet sizes (ping of death)	Half-open TCP connections add records to the TCPD server with pending connections, Simultaneous SYN packets from an unreachable host targeted to a machine (neptune)	D5	Vulnerable implementations of TCP/IP due to the data structure size used for storing incoming connections and the timeout value of half-open connections
		Receiving oversized IP packets, Systems crashing, freezing, and rebooting, Noting ICMP packet sizes (ping of death)	D6	Flagging ICMP packets > 64000 bytes.

Attack Behavior	Fault	Fault ID	Cause
	Large number of active connections on a port, Network services that forking or allocating new processes for incoming TCP/IP connections (process table)	D7	Completely filling a target machine's process table with multiple instances of network servers, as incoming TCP/IP connections are usually handled by servers running as root
	ICMP echo request packets flooded to IP broadcast addresses from remote locations but none originating from the victim machine (smurf)	D8	Amplifying requests with broadcast addresses upto 255 times (upto 255 machines on an ethernet subnet)
	Two fragmented IP datagrams, first is a 0 offset fragment with a payload size N , with the $MF = 1$, second is the last fragment ($MF = 0$) with positive offset $> N$ and payload size $< N$ (teardrop)	D9	Vulnerability in older TCP/IP stacks, Poor handling of overlapping IP fragments by IP fragmentation and re-assembly code
	Network suffers congestion and slowdown, Spoofed inbound packets appearing to be originating within the subnet, Looping causes traffic transmission between the charger or echo port of the two machines (udpstorm)	D10	Unauthorized account access, Single spoofed packet capable of creating a loop, Continues until restarting the INETD daemon

Table A2 RCA framework for Distributed Denial of Service (DDoS)

Attack	Behavior	Fault	Fault ID	Cause
DDoS	Large incoming network traffic from multiple HetIoT clients to a server IP with all IoT devices following specific traffic pattern, Closely grouped and coordinated behavior of bots, Communication with large number of devices, and Varying destination IPs between time windows	Testing specific credentials in specific ports, Downloading specific type of binary code, Exchanging keep-alive messages, Attacks with specific structures, Generating attack traffic with very few random elements, Infecting through TCP (23-2323, 7547) ports, Larger TCP traffic share, Smaller packet sizes and very small inter-packet interval (mirai)	DD1	Unsecure remote router access from ISP through port 7547, Webcam vulnerabilities allowing access through port 81, UPnP vulnerability in client router, and Webcam zero-day vulnerability allowing password file access
		Distributed communication through BitTorrent DHT and IP discovery through uTorrent transport protocols, RC4 message encryption, Larger TCP traffic share, Smaller packet sizes and very small inter-packet interval (hajime)	DD2	No malicious behavior, Closes potential IoT vulnerabilities, Potential zero-day exploit
		Exploiting SSH service default credentials, misconfigurations, and known vulnerabilities—inflicting PDoS, Defacing server firmware, Erasing files and reconfiguring network parameters, Continuous deployment and poor management of IoT devices, Improper device placements and allowing considerable traffic processing, Minimal interactions, Larger TCP traffic share, Smaller packet sizes and very small inter-packet interval (busy box)	DD3	Malwares are light-weight and need less resources to execute, Compatible across multiple platforms, Newer botnets are stealthier
		Sudden surge in network traffic, Traffic rate is between low-rate and high-rate DDoS, Larger UDP traffic share, Larger packet sizes and inter-packet interval (flash event)	DD4	Legitimate but harmful traffic, Lack of optimal traffic management and resource allocation policies

Attack	Behavior	Fault	Fault ID	Cause
Application layer DDoS	Disrupting legitimate server resources, Less bandwidth consumption and stealthy operation, and Targeting specific characteristics of applications	Disrupting legitimate user connectivity with spoofed or non-spoofed UDP, ICMP, DNS, or VoIP flood (flooding)	DD5	Exhausted network bandwidth of the victim
		Sending forged protocol requests to reflectors with victim IP (reflection)	DD6	”
		Consuming victim’s resources via TCP SYN flood, TCP SYN-ACK flood, ACK and Push-ACK flood, or RST/FIN flood (protocol exploitation)	DD7	Exploiting vulnerabilities in protocol implementations
		Bots generating large messages or multiple messages for each message, targeted to victim IP (amplification)	DD8	Exploited IP services
		Requests from spoofed IP sources—reflection to a large number of reflectors—amplification (smurf)	DD9	Exploited packet IP broadcast feature
		Generating large volume of small DNS queries with forged IPs (DNS flooding)	DD10	DNS response message size >> DNS query message size

Attack Behavior	Fault	Fault ID	Cause
Sessions containing high-workload requests (asymmetric)	Sending spoofed VoIP packets through SIP, Very high packet rate and very large random or fixed source IP range (VoIP flooding)	DD11	Victim VoIP server distinguishing the proper VoIP connections from the forged ones consumes excess resources, Unchanged source IP in VoIP flooding mimics Normal traffic and is difficult to distinguish.
	Session connection request rates from the attackers > legitimate users – HTTP get/post flooding or excessive VERB (session flooding)	DD12	Non-spoofed HTTP get/post flooding attacks, Hard to detect.
	Variation of HTTP get/post flooding, Employing HTTP-1.1 feature to allow multiple requests within a single HTTP session (request flooding)	DD13	Attacker limiting the session rate of an HTTP attack, Bypass session rate limitation defense mechanisms
	Variation of HTTP get/post flood attack, Forming a single packet embedded with multiple requests, Non-sequential requests within a single HTTP session (multiple HTTP get/post flooding)	DD14	Maintaining high loads on the victim server with a low attack packet rate, Attacker nearly invisible to netflow anomaly detection techniques, Bypassing deep packet inspection techniques by carefully selecting the HTTP VERB
	Generating requests to lock up database queries – like SQL injections (faulty application)	DD15	Poorly designs or improper integration with databases, Heavy server resource consumption

Attack	Behavior	Fault	Fault ID	Cause
Botnet-based DDoS	Controlling the constituent network devices and making them behave abnormally	Partial HTTP requests that continuously and rapidly grow, slowly update, and never close, continues until all available sockets are taken up by these requests (slowloris)	DD16	Attackers' IP are usually not spoofed, Limited resources can affect the server
		HTTP connections held up for a long time without raising any alarms, similar to slowloris (fragmentation)	DD17	Non-spoofed bots establish a valid HTTP connection with a web server, Fragmenting legitimate HTTP packets into tiny fragments and sending them as slow as the server time out allows
		Sending complete HTTP header with "content-length" field of the post message body for benign traffic, Sending data to fill the message body at a rate of one byte every two minutes (slowpost)	DD18	Server waits for each message body to be completed while the attack grows rapidly
		Slowly reading the response instead of slowly sending the requests, Setting a smaller receive window-size than the target server's send buffer (slowreading)	DD19	TCP protocol maintains open connections even in idle data communication, Attacker forcing the server to keep a large number of connections open
		Stealthy C&C to bot communication via instant messaging – trinity with UDP, TCP SYN, TCP ACK, and TCP NUL floods and kaiten with UDP, TCP, SYN, and PUSH+ACH floods (IRC-based)	DD20	IRC can connect hundreds of clients via multiple servers, Using legitimate IRC ports to send commands to the bots and can easily hide his presence because of the large volume of IRC traffic, making it difficult to track, Easy to access the list of all the available bots instead of local list
		Periodically downloading the instructions using web requests with encrypted HTTP (port 80) or HTTPS (port 443) communications without connecting with C&C server (web-based)	DD21	Hide themselves within legitimate HTTP traffic, Configuring and controlling bots through complex encrypted PHP scripts and, Difficult to detect

Table A3 RCA framework for Reconnaissance (Recon)

Attack	Behavior	Fault	Fault ID	Cause
Recon	Large incoming network traffic across multiple Het-IoT 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
		DNS zone transfer of bruteforce scanning (mscan)	R2	"
		Traffic via TCP/UDP or via only FIN packets or via only SYN packets (nmap)	R3	Client unable to maintain active monitoring state for longer times
		DNS, RPC, unsecure NFS mount points, fingerd, ruserd, and boottd vulnerabilities on TCP (70, 80 FTP, Telnet, SMTP, NNTP, and UUCP) and UDP (DNS, 177) ports (saint)	R4	Exposed vulnerabilities in the system
		Subset of vulnerability checking in the following order: NFS export, NFS export via portmapper, NIS password file, REXD, TFTP file, Remote shell, X server, Writeable FTP home directory, Sendmail, and FTP (satan)	R5	"

Table A4 RCA framework for Theft

Attack	Behavior	Fault	Fault ID	Cause
Theft	Stealthy approach to evade detection, Constantly monitoring and interacting with compromised systems, Appearing similar to legitimate traffic	Advanced social engineering techniques, Obfuscated malwares, Backdoor communication with remote C&C via TCP port 443 (injection flaw)	T1	Encrypted traffic – difficult to inspect, Zero-day vulnerability in the Internet Explorer browser
		Remote C&C connection through remote access toolkit – RAT (RSA APT)	T2	Exploiting the RAT functionalities
		Emails appearing to be from trusted sources with spoofed URLs and malwares (phishing)	T3	Lack of security awareness among network users, Poor management of information on social networks, Need for effective monitoring
		Variant of phishing, Highly targeted and technically competent, Harder to implement and is effective (spear-phishing)	T4	”
			”	Improper access control mechanisms, Unupdated security policies, Need for log analysis, File integrity checking, Registry monitoring, Rootkit detection, IDS, Frequent vulnerability assessments,
		Exfiltrating data via TCP port 443 (aurora)	T5	Configuring the port to only allow the traffic from its own proxy, Using access-control lists to permit or deny traffic

Attack Behavior	Fault ID	Cause
Tapping the information that goes on the wire online or offline (eavesdropping)	T6	Allowing unencrypted, unauthenticated traffic
Impersonating sender and receiver to each other modifying the traffic in between, Passive or active (man-in-the-middle)	T7	"
		No hashing at edge devices
Copying and possibly modifying the data transmitted between two hosts (replay)	T8	No message timestamping and encrpn.
Breaking or guessing passwords through trial and error, Resource intensive but effective, Ineffective on online services (brue force)	T9	Poor authentication constraints
Attempting only a targeted list of weak passwords on a limited number of key combinations that has a high success probability (dictionary)	T10	Weak and predictable passwords, Unencrypted database authentications
Originating within the host network (insider)	T11	Devices not monitored for traffic behv.
Capturing user keystrokes through hardware device or software program (keylogger)	T12	Unencrypted keystrokes, No anti-logger programs
Basic keyloggers to advanced trojans through phishing (script kiddie)	T13	Lack of anti-malware and intrusion detection systems
Exploiting the TCP session between a web server and a browser and stealing the session tokens (session hijacking)	T14	Easy access to HTTP header, Poor cookie management, Lack of encrpn.
Monitoring and keylogging through social engineering (shoulder surfing)	T15	Predictable information and passwords