Reducing Computational Cost in IoT Cyber Security: Case Study of Artificial Immune System Algorithm

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Abstract: Using Machine Learning (ML) for Internet of Things (IoT) security monitoring is a challenge. This is due to their resource constraint nature that limits the deployment of resource-hungry monitoring algorithms. Therefore, the aim of this paper is to investigate resource consumption reduction of ML algorithms in IoT security monitoring. This paper starts with an empirical analysis of resource consumption of Artificial Immune System (AIS) algorithm, and then employs carefully selected feature reduction techniques to reduce the computational cost of running the algorithm. The proposed approach significantly reduces computational cost as illustrated in the paper. We validate our results using two benchmarks and one purposefully simulated data set.

1 INTRODUCTION

IoT is expected to usher in an era of increased connectivity, with an estimated 50 billion devices expected to be connected to the Internet by 2020 (Aazam et al., 2018). At its core, the aim of the IoT is to connect previously unconnected devices to the Internet. Thus, creating smart devices capable of collecting, storing and sharing data, without requiring human interaction. Many of these IoT devices, made up of tiny electronic units that consume much of the available system resources, are aimed at nontechnical consumers, who value low cost and ease of deployment. This has led to some IoT manufacturers omitting critical security features, and producing insecure Internet-connected devices. Such insecurities are often derived and epitomized by inherent limitations of computational resources, lack of convenient user interface, use of default credentials and insecure protocols. By comprising multitudes of these vulnerable IoT devices, attackers can now perform large scale attacks such as spamming, phishing and Distributed Denial of Service (DDoS), against resources on the Internet (Moganedi and Mtsweni, 2017). IoT technology has the potential to become a new playground for future cyber attacks and therefore presents a number of challenges.

Several Machine Learning (ML) techniques had been proposed for security monitoring in the spectrum of cyber security; however, due to the resource-constrained nature of IoT, most of these techniques cannot be directly deployed on these devices, making resource management a considerably challenging issue for IoT devices. The aim of this paper is to investigate how to reduce resource consumption of ML algorithms in security monitoring of IoT devices. For this purpose, we employ carefully selected feature reduction techniques in ML, and then empirically validate our approach using the Artificial Immune System (AIS) algorithm utilizing two benchmark security data sets (Meidan et al., 2018; Al Tobi and Duncan, 2018) and one carefully tailored data set. The proposed approach has reduced the memory usage and running time of the ML technique chosen in this paper for security monitoring.

The rest of this paper is organized as follows. Related work is presented in Section 2. Then the theoretical background is presented in Section 3. The practical experiments and results are then presented in Section 4 and 5, respectively. Finally, a conclusion is presented in Section 6.

2 RELATED WORK

There are various works in the field of IoT from the perspectives of security, architecture, deployment op-

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portunities and resources management (Farooq et al., 2015). Authors in (Nskh et al., 2016) have employed dimensional reduction technique with a Support Vector Machine (SVM) classifier for intrusion detection based on the KDD 99 data sets. Pajouh in (Pajouh et al., 2016) proposed a similar method, but based on the NSL-KDD 99 data set, and described a theoretical approach for determining computational complexity. Authors in (Fekade et al., 2018) and (Lopez-Martin et al., 2017) have implemented the IoT data recovery methods for intrusion detection. Reducing the number of features within the data set has shown an improved performance. Their scheme was capable of saving memory requirement among sensors at the architecture level. Also, Memos in (Memos et al., 2018) proposed an algorithm for IoT security.

An enhancement of an AIS algorithm has been proposed in (Liśkiewicz and Textor, 2010) without generating detectors, and the run time complexity expanded from polynomial to exponential. In (Nskh et al., 2016), there is neither experimental record for calculating the computational complexity, nor a theoretical description. Most of the previous implementations were conducted using the oldest KDD 99 data set that has been regarded as an outdated data sets. From the literature, only a few researchers tested the overall records of the KDD 99 data using the AIS algorithm due to the implementation complexity. In this paper, we focus on reducing the overall computational cost of running monitoring algorithms using AIS as a case study. The integrated resource reduction techniques are capable of reducing the required memory resources and processor running time in an embedded IoT devices.

3 THEORETICAL BACKGROUND

Recent development in IoT cyber security and higher dimensionality of data resulted to the increase in volume, velocity, and variety requires careful deployment of feature reduction techniques. Promisingly, feature reduction method can improve the efficiency of ML algorithms.

3.1 Artificial Immune System

Computer scientists have been inspired by the biological systems in developing techniques for solving problems. Pamukov in (Pamukov and Poulkov, 2017) applied Negative Selection Algorithm (NSA) from an AIS for IoT intrusion while, Zhuo in (Zhu et al., 2017) employed NSA for classification task. This algorithm, trains a population of antibodies called detectors using a normal sample from the population. A Real Value Negative Selection Algorithm (RNSA) generates random detectors and tests them against the sample of the self-class for affinity measure. Affinity is measured based on distances as Euclidean, Manhattan, or Cosine. There is no perfect shape for an antibody as long as it can be implemented; however, RNSA has been implemented using a hypersphere antibody. In this work, we employed RNSA as the selected AIS algorithm.

In the implementation of RNSA using real value data sets, it makes sense to view every vector as its location within the shape space. While working with the data, each element in a vector corresponds to a specific feature in the data sets. This makes it easier to normalize the values in the data within the range of [0, 1]; thus, each feature vector is now associated with a point in the shape space. In the case of the RNSA algorithm that handles numerical data, the shape space (as well as the feature vector values) are continuous. Formally, Eq. 1 has notated the RNSA.

$$X = R^d \tag{1}$$

where $X \in \{x_1, x_2, x_3, ..., x_d\}$ is the total sample, R is the real valued data field, and d is the number of dimensions. Moreover, $Y \in \{y_1, y_2, y_3, ..., y_n\}$ represents the class label of the sample in a space having n dimension.

3.2 Resource Reduction

Resource reduction is important before passing the data to a ML algorithm. The rationale is to extract useful features only from a huge amount of available data, in order to alleviate over-fitting and noise.

(i) Principal Component Analysis (PCA)

PCA, known as the *Karhunen-Loeve*, is a statistical procedure that transform an observed set of possibly correlated variables into a set of values of linearly uncorrelated variables, called principal components. The number of decomposed principal components are fewer than, or equal to, the original number of variables. The rational for PCA is to identify the subspace in which the data clusters. For instance, an n dimensional data observation might be confined into into an $n-1$ distinct principal components. Such capability in data reduction, while retaining most of the variation presents in the original data, has made PCA useful. Hong in (Hoang and Nguyen, 2018) applied PCA using substantial data sample for IoT anomaly detection.

In this research, PCA has been integrated with the RNSA algorithm as an approach of reducing resource consumption in processing IoT data. The argument raised is whether the computational cost of applying PCA data brings any advantage in comparison with processing the original data.

(ii) Gini Index (GI)

GI is an inductive decision tree algorithm based on impurity function, called *gini index*, for finding the best split. GI method explores the relatives distribution of a feature among classes and it is a useful resource reduction method. This technique was developed by an Italian sociologist and statistician called *Corrado Gini* in 1912. The main idea is to measure the statistical dispersion of income across various populations. The methods has been widely adapted in the IoT research for purifying important features as in (Liu et al., 2018). The *Gini, G* for a data set S having m subset $S \in \{s_1, s_2, s_3, ..., s_m\}$ with j different classes $C \in \{c_1, c_2, c_3, ..., c_j\}$, is defined in Eq. 2.

$$G(S) = 1 - \sum_{j=1}^{m} P_j^2 \tag{2}$$

where, P_j is the rate of class C_j in S; S can be split into n subsets, as described in Eq. 3. The split with the best value among classes is chosen - this process is referred to as feature impurity gain score. The range of the splits of $G_{split}(S)$ is between [0, 1].

$$G_{split}(S) = \sum_{i=1}^{n} \frac{s_i}{s} Gini(S_i) \tag{3}$$

In this work we integrate *GI* with the RNSA algorithm as an approach to extract highly relevant features in the IoT and KDD 99 data.

4 EXPERIMENTAL PROCEDURE

In the presented paper the integrated resource reduction approach has been implemented along with the RNSA algorithm using a hypersphere. In this implementation, each hypersphere present in the shape space has the same number of dimensions as the data. The hypersphere has been parameterized by the length of a vector representing a record in space. Each hypersphere is defined with a real-valued radius as well as the class label that represent the class of a detector. The benchmark data sets investigated in this research are real-valued and have been normalized within the range of [0,1] by the *Min-Max* normalization formula presented in Eq. 4.

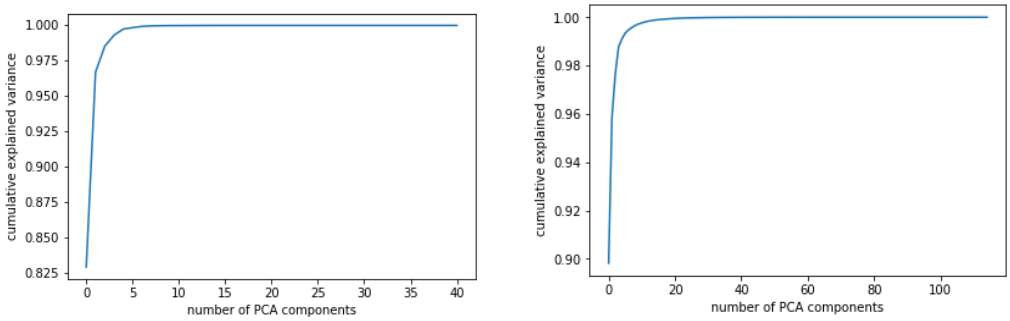
$$Norm(x) = \frac{x - X_{min}}{X_{max} - X_{min}} \tag{4}$$

where $x \in X$ represents the value of vector X, while X_{max} and X_{min} represents the maximum and minimum values of the vector X. The normalization helps in selecting the detector radius as the threshold parameter used to separate normal and abnormal data. The GI was implemented with a random forest classifier in selecting higher ranking features, while the PCA implementation was designed to observe relevant features with a significant variance ratio.

The simulated artificial data, IoT-Doorbell in (Meidan et al., 2018) and KDD-99 data sets in (Al Tobi and Duncan, 2018), were tested and examined. The KDD and IoT data sets are publicly available for downloading from the UCI repository. The IoT-Doorbell data set is one of the recent cyber security data sets released in 2018 as described in (Meidan et al., 2018). This data set has 1,572,333 data samples and 116 features, including the class label - attacks as '0's, and the normal as '1'. The records are for both benign and malicious traffic, and each record represents a traffic flow from a real network. The KDD-99 data set presented in has 494,022 different records for both types of traffic. The artificial data set was randomly generated with 1,000 records, using the normal distribution, and it has 2 features. A series of experiments have been conducted to analyze the computational complexity with respect to the features' contribution to the resource reduction implemented in this paper. The IoT-Doorbell data set was tested using the full and sub-feature samples. The data set has been checked for missing values and duplicates before the implementation and it was splits into two portions, 80% and 20% for training and testing, respectively.

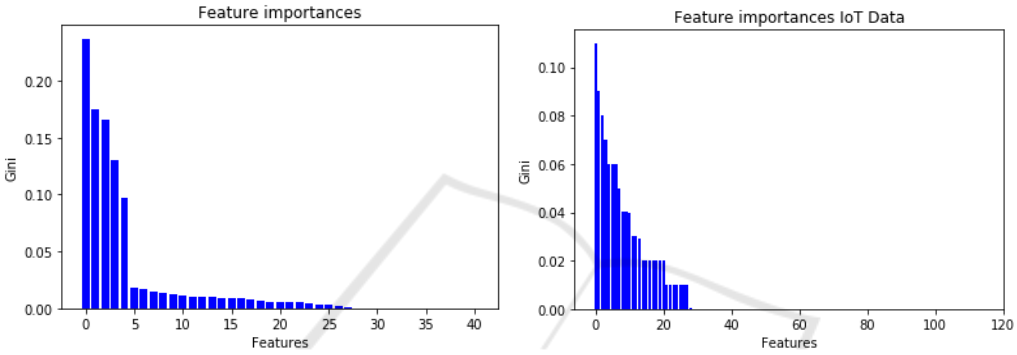
Experimental records are investigated based on the deterministic properties of the IoT features in terms of resource minimization, the overall amount of IoT data, and the reductions achieved. The test was carried out on Xeon E5 processor at $3GHz$, and the memory utilization has been observed using the memory profiler of the Python module adopted. All experiments described in this paper were conducted using the *Spyder* scientific integrated Python environment.

A series of experiments have been conducted to analyze the performance of the integrated resource reduction approach in terms of detection accuracy. Experiments were performed ten times with the radius varied from 0 to 1, with an increase step of 0.1. Initially, an experimental results with the artificial data set have been examined and recorded under different threshold values. Then, the IoT and the KDD-99 data were also tested and evaluated. The test with the



(a) (b)

Figure 1: PCA Components for (a) KDD Data and (b) IoT Data.



(a) (b)

Figure 2: Gini Index feature importance for (a) KDD Data and (b) IoT Data.

KDD-99 data was compared with the rest, where the normal traffic samples are labelled as '1' and all other attack traffic data are labelled as '0'.

5 EXPERIMENTAL RESULTS

This section presents the results of the experiments run for the implementation of the resource reduction techniques described in this paper. Fig.1a and b illustrate the PCA variance ratio of the KDD and IoT data sets, respectively. The PCA transformation has indicated that using only 10 to 20 principal components from the IoT data, about 99% of the variance ratio was retained. Moreover, Fig.2a and b illustrate the GI features of the KDD and IoT data sets, respectively. It is apparent that using only 26 GI features from the entire IoT data can be sufficient to build our ML model.

Results in Table 1 provide the accuracy values of the anomaly detection using the data sets considered in this paper, with and without feature reduction. The results reveal that the artificial data set with 2 features has the highest accuracy of 100%. This is because the two features are highly distinctive from each other. Interestingly, the feature reduction techniques used on both IoT and KDD data sets do not decrease the accuracy of detection compared with using the entire data set. An equal detection accuracy of 68% is achieved using the full data set, 10-20 PCA, and 26 GI for the IoT data set, and an accuracy of 80% is achieved using the full data set, 5 PCA, and 11 GI for the KDD data set. This validates the results presented in Fig. 1 and 2 and supports the argument of using feature reduction for resource utilization the detection accuracy is not decreased.

Table 1: Experiments and Data Sets.

Data Sets	Features	PCA	Gini	Accuracy (%)
Synthetic Data	2	N/A	N/A	100
Ba IoT	115	N/A	N/A	68.30
	20	✓	N/A	68.80
	15	✓	N/A	68.50
	10	✓	N/A	68.60
	26	N/A	✓	68.50
KDD 99	41	N/A	N/A	80.00
	11	N/A	✓	80.10
	5	✓	N/A	80.25

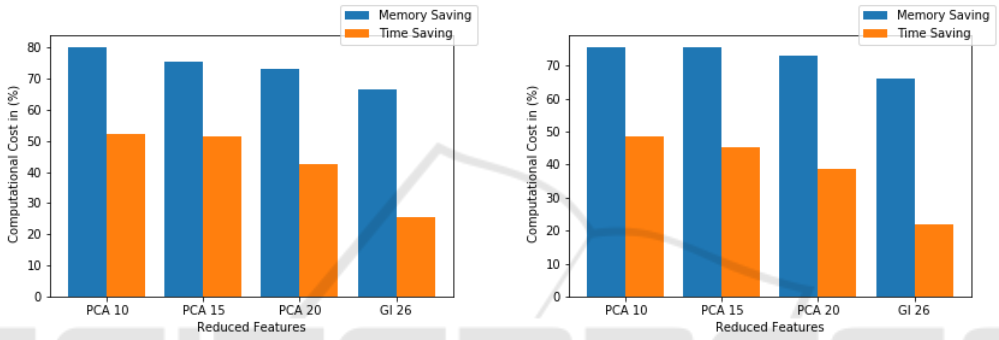
Table 2 provides results of the training and testing memory consumption, with and without using

Table 2: Computational Memory Comparisons.

Computation	PCA 10	PCA 15	PCA 20	GI 26	Full Features
Training in MB/Sec	233.2	285.8	317.0	393.9	1169.4
Testing in MB/Sec	233.4	286.2	317.5	396.3	1172.7
Training Saved in %	80.06	75.56	72.89	66.32	N/A
Testing Saved in %	80.09	75.59	72.93	66.21	N/A

Table 3: Computational Time Comparisons.

Computation	PCA 10	PCA 15	PCA 20	GI 26	Full Features
Training in minutes	1920.2	2100.4	2340.1	3040.2	4080.2
Testing in minutes	960.6	1020.2	1140.5	1450.6	1860.2
Training Saved in %	52.0	51.4	42.6	25.5	N/A
Testing Saved in %	48.4	45.2	38.7	22.0	N/A



(a) (b)

Figure 3: Computational cost saving comparison in (a) Training and (b) Testing.

feature reduction of the IoT data set. The memory consumption for the AIS training phase using the complete IoT data set is 1,169.4 MB/sec, compared to 233.2 MB/sec using 10 PCA components, and 393.9 MB/sec using 26 GI features. Moreover, the memory consumption for the AIS testing using the complete data set is 1172.7 MB/sec, compared with 233.4 MB/sec using 10 PCA components, and 396.3 MB/sec using 26 GI features. Therefore, the highest saving of 80% for both training and testing is achieved by using 10 PCA, which is due to using the lowest amount of features that capture all the variance in the data set.

The running time of AIS algorithm, with and without feature reduction, is presented in Table 3. Considering the 10, 15, and 20 PCA components and the 26 GI features, the running time is lowest in the case of using 10 PCA components compared with the remaining feature reduction approaches, with a total saving of 52% and 48% for the training and testing phases, respectively. The resulting saving of both memory consumption and processing time is presented in Fig. 3.

The analyzed results reveal considerable reductions in the memory consumption and processing time when using smaller data features. These results demonstrate the capability of the proposed approach in utilizing and managing ML resources.

6 CONCLUSION

In this paper, resource utilization for lower computational cost of ML algorithms in IoT security monitoring is investigated. This is based on feature reduction methods, particularly the principal component analysis and Gini index techniques. An empirical validation of the proposed approach was presented using the Artificial Immune System (AIS) algorithm, utilizing two benchmark security data sets, which are the KDD 99 and IoT-Doorbell, and one carefully tailored data set.

Results have demonstrated that feature reduction techniques have lead to significant savings on both memory consumption and processing time. The highest saving occurred by using 10 PCA components, compared with 15 and 20 PCA components, and GI techniques. The savings have reached up to 80% and 52% for memory consumption and processing time, respectively. Providing recommendation of us-

ing PCA over GI for further feature reduction and computational cost savings for the considered scenarios.

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