The Cuckoo Feature Filtration Method for Intrusion Detection (Cuckoo-ID)

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Abstract—Intrusion Detection Systems (IDSs) play a crucial role in keeping online systems secure from attacks. However, these systems usually face the challenge of needing to handle and analyze a vast volume of data in order to achieve intrusion detection. Feature filtration is a solution that overcomes this challenge by focusing on the characteristic network features that play a significant role in enabling these systems to achieve high detection rates. This paper presents an intelligent cuckoo feature filtration method that is intended to prune away insignificant network features. Then, an IDS (the Cuckoo-ID) is designed in which an eXtended Classifier System (XCS) uses the filtered features for improving the rate of detection of network intrusions. Thus, the main objective of Cuckoo-ID is to maximize the detection rate (DR) and minimize the false alarm rate (FAR). Experiments were then run on the KDDcup'99 dataset to test the intrusion detection (ID) efficiency of the proposed system. The results showed that cuckoo filtration does profoundly raise the ID rate of the entire system. Finally, the DR and FAR of Cuckoo-ID were compared with those of intrusion detection methods that depend on network feature filtration.

Keywords—Cuckoo algorithm; feature filtration; intrusion detection; XCS; detection rate

I. INTRODUCTION

More lights have been spotted recently than before on the networks because of the sensitivity of such an environment. The networks have a vast number of resources and information. Therefore, protective solutions against possible threats and vulnerabilities of mechanisms must be implemented.

Now, an Intrusion Detection System (IDS) is one of the popular mechanisms for protecting network resources against attacks [1]. James Anderson, in 1980, published the first study of IDSs for improving the security levels of networks [2]. The IDS has been defined by Teodoro [3] as being ‘a security tool, like other measures such as antivirus software and firewalls proposed for security, to enable that security to become more powerful, in terms of protecting an information and communication system’. Therefore, intrusion detection (ID) aims at achieving intelligent control of the events occurring in a. Researchers in [1,4,5] have explained that the IDSs have two major taxonomies, depending on the source of the data to collect. These are:

- Host-based Intrusion Detection System (HIDS) which are targeted to collect information about activity in a specific host [5].
- Network-based Intrusion Detection System (NIDS) which collect information from the network [5].

Different Artificial Intelligence (AI) techniques including Deep Learning, Cuckoo Algorithm, Fuzzy Logic, Genetic Algorithm, and the Artificial Neural Network have been applied and enhanced to automatically detect possible intrusions [6, 7, 8]. Furthermore, different AI techniques have been adapted to identify the key and most relevant network features that guide and lead the IDS to achieve accurate detection as in Jamali and Jafarzadeh [9]; Lee, Park, and Lee [10]; Abd Eldayem [11]; and Alsharafat [12]. Within this context, feature filtration has the crucial advantage of overcoming the conflict between network features and attacks.

Bearing this in mind, this study was initiated to assess the potential for the Cuckoo Algorithm to serve as a feature filtration method that will reduce the number of the network features needed to detect intrusion; Determine the impact of feature filtration on ID and Compare the level of ID performance of the proposed feature filtration method (Cuckoo-ID) with those of other ID methods (both the ones involving feature filtration and those which do not).

In short, the key contributions of this work are enumerated as follows.

1) Summarize a set of interrelated works related to IDS and those involving feature filtration.
2) Propose a new feature filtration method for intrusion detection system based on Cuckoo Algorithm.
3) Implement an intrusion detection model that applied the Cuckoo algorithm for feature filtration.
4) Evaluate the performance of the proposed feature filtration method and compare the result with methods involving feature filtration and those which do not.

The remainder of this paper is organized as follows. Section 2 reviews related to previous works. Section 3 describes the benchmark dataset that is widely used in testing the levels of performance of IDSs. Section 4 clarifies the proposed method for improving ID. Section 5 discusses the evaluation of the performance of the proposed ID method. Lastly, Section 6 contains a discussion of the experimental results and concludes them.

II. RELATED WORKS

A review of the published literature reveals that different researchers have employed various AI techniques for ID [6 – 20]. These techniques include Artificial Neural Networks (ANNs), the Cuckoo Algorithm, Fuzzy logic, metaheuristic algorithm, Random forest, cuttlefish algorithm, and the Genetic Algorithm (GA), besides other new trends to be
implemented in detecting network attacks, especially in the environment of the Cloud, which is regarded by intruders as being a preferred target with regard to exploiting its weak points.

Some researchers keenly delved into a search for key factors that have a positive influence on DR. In this regard, the search was guided (in some studies) by the investigation of the effect of network feature filtration on the proposed IDS [6–20]. For feature filtration, Alsharafat in 2010 [12] has developed an ID model called ANN-XCS that proceeds in two phases. The first phase concerned about feature filtration by applying AN. Then, the filtered features will be considered in the entire work of the second phase, which applied an Extended Classifier System (XCS) for the purpose of intrusion detection. For enhancement, XCS applies a set of modifications to GA for the breeding classifier pool. As a result, the DR of ANN-XCS was 98.01%, and the concomitant FAR was 0.9%.

Alzboon, Alkhaldy, and Alsharafat [13] proposed an IDS in 2017 that was based on using the Cuckoo search method integrated with GA as a classifier generator within XCS. In addition, the network features were filtered in this system using Fuzzy Clustering by the Local Approximation Membership (FLAME) method, FLAME-XCS as an abbreviation, which reduced the number of network features to track from 41 to 20 features. As a result, the DR reached 99.9% while the FAR reached 0.005%, corresponding to an outstanding ID efficiency.

A Learning Automata Intrusion Detection System (LA-IDS) was developed in 2017 by Jamali and Jafarzadeh [9]. This model applies a seven-level hierarchical structure in which each level is responsible for processing one of the network features. By reducing the number of features to trace from 41 to 7, this system (LA-IDS) proved to have a DR of 98.9% and a FAR of 1.3%. In the same year, Lee, Park, and Lee [10] focused on feature selection, which represents the first phase of the proposed work, which aimed at constructing a subset of features using a sequential, forward-floating search (SFFS) instead of the method used by Jamali and Jafarzadeh [9]. The second phase of the proposed system, however, entailed the construction of a classification model based on using a random forest classifier (RFC) to select a feature subset. Lee in his work achieved 99.9 as DR and 0.1 as FAR. In another study, an optimization technique, the Naïve Bayes (NB) classifier, was applied by Abd-Eldayem in 2014. Experimentation revealed that this optimization technique had a DR of about 99% and a FAR of nearly 1%.

In 2018, Shone and his colleagues [6] proposed a novel deep-learning (DL) classification model that was constructed using stacked, non-symmetric, deep auto-encoder a multiple, hidden-layer, unsupervised, neural network-based, feature extraction algorithm. This model had a DR of 97.9% and a FAR of 2.1%.

Also, Yan and Han [8] proposed an IDS which would use the stacked sparse auto-encoder (SSAE) for extracting the features that have a significant influence on intrusion behavior. Then, a different classifier was employed by using low-dimensional sparse features. Performance evaluation revealed that this model had a DR of 99.01% and a FAR of 0.13%.

In 2019, Sara and her colleagues [18] proposes a wrapper method for feature selection based on linear correlation coefficient (FGLCC) algorithm and cuttlefish algorithm (CFA), and the Decision tree act as a classifier in IDS. The results obtained DR equals 95.23% with a low FAR of 1.65%. Also, Boonyopakorn in 2019 has applied Fuzzy logic and association with genetic network programming (GNP), FL-GNP as an abbreviation, for feature selection to create an associated rule to detect attacks [19]. Thus 24 features used instead of 41 features which produced an IDS with a 94.8 detection rate.

Convolutional neural network (CNN) has been applied by Xiao in 2019 [20] in detecting network attacks which called (CNN–IDS). The auto-encoder (AE) as a nonlinear dimension reduction technique has been used to reduce features. The overall DR and FAR were 93.0 and 0.005, respectively.

The pigeon inspired optimizer algorithm was proposed [16] by utilizing the selection process of network features. A new methodology used to binarize a continuously metaheuristic algorithm. Also, the proposed work, externally, compared with the sigmoid function. As a result, the accuracy of detection was 0.947. While Aishwarya and his colleagues [17] examine the efficiency of J48, Naïve Bayes (NB) and Random forest (RF) as a classification models. The RF reached 99.9 and 0.004 as a DR and FAR, respectively.

III. THE KDD’99 DATASET

For assessing the performance of the proposed Cuckoo-ID system, there was a need to run it on actual data. For this purpose, the researcher utilized the KDD99[21] dataset, which is (so far as the author knows) the most appropriate dataset for this purpose. KDD’99 is a benchmark dataset that is frequently used by different researchers to evaluate the levels of performance of their proposed IDSs.

The origin of KDD’99 is DARPA, which produced it in MIT Lincoln Labs. This dataset is a standard dataset that is commonly used to evaluate results in this line of research. A standard set of data needs to be audited, since it includes a huge number of intrusion records that have been simulated in a military network Laboratories [21]. In this respect, the analysis of the KDD’99 provides useful information for the expansion of IDSs. The data in this dataset are classified into normal records and attack records, and they involve mining rules. This dataset contains 41 features. Hence, one of the objectives of the feature filtration method is its ability to extract the most relevant set of features. In this context, different algorithms can be applied to select the relevant features from the KDD’99 dataset, as in Jamali and Jafarzadeh [9]; Lee, Park, and Lee [10]; Abd-Eldayem[11]; and Alsharafat [12].
IV. PROPOSED WORK

Here, a new IDS will be presented by adapting a Cuckoo Algorithm to include feature filtration, which is due to working overall the XCS steps. The Cuckoo Algorithm is used in the present study as a feature filtration method to enhance the detection of the network attacks. The motivation for performing this work emerged from the high potential of this particular algorithm for feature filtration as had been confirmed in various previous studies such as Gandomi, Yang, and Alavi [22]; Yang and Deb [23]; and Yang, Deb, Karamanoglu, and Xingshi [24]. In 2009, Yang and Deb [23] presented this meta-heuristic algorithm—namely, the Cuckoo Algorithm—which they based on a parasitic-like nesting behavior for the brooding of some cuckoo species. This algorithm works coherently and effectively with the Lévy flights (LFs). Thus, the general framework of the proposed work consists of two key processes; feature filtration using a cuckoo algorithm which specifies the key features that are considered next process which concerns about intrusion detection using XCS as illustrated in Fig. 1.

A. Cuckoo Feature Filtration

One of the critical decisions in any IDS is the selection of the critical network features. Thus, for enhancing the detection of the proposed method, the cuckoo algorithm was employed as it plays an important role in distinguishing the features that will seriously affect the performance of the system. This algorithm increases the DR and reduces the associated FAR. In addition to this, the Cuckoo Algorithm works effectively with Lévy Flight (LF) and generates new solutions around the most suitable solution obtained so far, which will speed up the process of local search [22–26].

The solution-generation process of the cuckoo search algorithm depends on three rules:

- Each cuckoo randomly chooses a nest in which to lay one egg at a time.
- The elitism nests with high-quality eggs will be transferred to the next generation.
- The number of host nests is fixed, where each host can detect a strange egg with a probability of $P_a \in [0,1]$. As well, the host bird can discard the egg or leave the nest to construct a new nest in another place [23]. For such enhancements, certain characteristics of the current solution must be modified in order to breed a new solution.

The Cuckoo Algorithm for feature filtration can be summarized in the follow Pseudo-code as in Fig. 2 [23,26]:

By incorporating the LF in the Cuckoo Algorithm, the LF will guarantee to find new solutions in the region of the best-stated solution, which will boost the speed of the local search space [23,25,26] and guarantee that the system will not be trapped in a local optimum [22,23].

B. Extended Classifier System (XCS)

In 1995, Wilson has introduced The XCS[27], which is a real (integer or binary) code one of the Learning Classifier System categories. It is a fitness classifier system in which every rule depends on a fitness value for the evaluation of this system. As such, the XCSs can be classified as a rule-based classifier system. Each rule, or classifier, is constructed from two parts:

1) The Condition Part: This part is encoded using the step size parameter ($\alpha$). So, a binary code is applied by using the notion of $\{0,1,\#\}$, where the symbol $\#$ refers to a non-significant value of a feature.

2) The Action Part: This part represents the result of the selected rule that will be fired at the environment. The result can be either a normal record or an attack.

Thus, in all XCS components, the filtered features produced from applying the cuckoo algorithm will be considered in condition part in every rule(classifier) through population set $P$, matching set $M$, prediction set and action set $A$.

The XCS concentrated on two main operations: Reinforcement Learning (RL) and GA breeding. RL is concerned with gaining criticism from the external environment about the fired result. It is also concerned with taking advantage of the selected rule in order to be useful in similar situations [28,29]. On the other hand, the GA is used for breeding new rules.

![Fig. 1. The Proposed Work; Cuckoo Algorithm and XCS.](image-url)
The main components of the XCSs are as follows [27–30]:

- **Detector**: The detector is an input gateway that considers the environment as being a traffic record to be converted into a binary code. Here, the filtered feature will be encoded using binary code while other features replaced by sign (_) to represent irrelevant features in detection.

- **Match set [M]**: The match set is a repository of the rules that are compiled after performing matching between system rules and records (population of rules [P]) via the detector according to the conditional part, regardless of the action result.

- **Prediction Array**: The prediction array is an array created from [M] according to the average weighted fitness of the prediction rules employed in an action set [A].

- **Action set [A]**: All the rules in [M] that support a specific action will be placed in an [A].

- **Effectors**: The effectors are output gateways for a rule-selected form [A]. They are intended to determine whether the traffic record is a normal record or an attack.

V. PERFORMANCE EVALUATION

For evaluating the performance of the proposed IDS and comparing it with levels of performance of comparable IDSs, two performance evaluation criteria were employed; the DR and the FAR.

- **Detection rate (DR)**

  The detection rate (DR) has been defined as ‘the ratio between the number of correctly detected attacks and the total number of attacks’ [31]. This ratio is calculated as a percentage using Equation (1) [13,14]:

  \[
  \text{DR} = \frac{(TP)}{(TP + FP)} \times 100 \%
  \]  

  (1)

- **False alarm rate (FAR)**

  The false alarm rate (FAR) has been defined as being ‘the number of “normal” patterns classified as attacks (False Positive) divided by the total number of “normal” patterns’ [31]. It is usually expressed as percentage and can be estimated using Equation (2) [13,14]:

  \[
  \text{FAR} = \frac{(FP)}{(FP + TN)} \times 100\%
  \]  

  (2)

  The definition of the entire parameters in equation (1) and (2) are listed in Table I.

| Parameter          | Definition                                                                 |
|--------------------|-----------------------------------------------------------------------------|
| True Positive (TP) | Attack records correctly classified as an attack.                           |
| False Positive (FP)| Normal record that is inaccurately classified as an attack.                |
| True Negative (TN) | Normal record that is correctly classified as normal.                       |
| False Negative (FN)| Attack record that is inaccurately classified as normal.                   |
VI. EXPERIMENTAL RESULTS AND CONCLUSION

One of the aims of the IDS proposed in this study is the enhancement of feature filtration in the ID process. Feature filtration aims at selecting the features that have a crucial role in the detection of each type of attack. Thus, the Cuckoo Algorithm was employed to achieve this purpose.

A comparison was held between different IDSs employing feature selection methods enhancing the efficiency of ID in terms of the DR and FAR. Comparisons in terms of the DR and FAR are shown in Table II, whereas comparisons in terms of the DR alone are illustrated by Fig. 3. It should be underscored first that the number of features identified by the different filtration methods as crucial to ID was different, varying from 7 to 41 features (Table II and Fig. 1).

In terms of the DR, it can be noticed that the IDS proposed in this study (Cuckoo-ID) has an equal performance to that LA-ID developed by Jamali [9] and a somewhat better performance (i.e. higher DR) than the ANN-XCS suggested by Alsharafat [12]. In the meantime, SFFS[10], BN in Abd-Eldayem [11], and FLAME-XCS [13] slightly outperform the system proposed in the current study (Table II and Fig. 1).

In terms of the FAR, it is found (Table II) that the IDS suggested in the present study ranks third in performance next to the sy...
TABLE III. A COMPARISON IN PERFORMANCE BETWEEN THE PROPOSED CUCKOO-IDS AND IDS WITH NO FEATURE SELECTION IN TERMS OF DR AND FAR

| IDS              | DR (%) | FAR (%) |
|------------------|--------|---------|
| SCDNN[33]        | 92.23  | 7.9     |
| TLMD 4 [34]      | 93.11  | 0.761   |
| DENDRON [35]     | 95.97  | 1.08    |
| CNN+LSTM[36]     | 96.96  | 0.2     |
| DEEP [6]         | 97.9   | 2.1     |
| RF [17]          | 98.7   | NA      |
| Cuckoo-ID        | 98.9   | 0.09    |
| LA-GRU[7]        | 98.9   | 0.134   |
| ECOC[32]         | 99     | NA      |
| Stacked [8]      | 99.01  | 0.13    |

Table III and Fig. 4 points out that, in terms of the DR, Cuckoo-ID and LA-GRU[7], which both have the same DR (98.9%), rank third in performance next to the Stacked method [9] whose DR was 99.01% and ECOC method [32] whose DR was 99.00%. Again, this result supports that the researcher’s own proposed IDS has noticeably good performance and is promising, owing to the fact that it performs better in terms of the DR than several previous IDSs have done (Table III).

In other respects, the comparison between the IDSs listed in Table III in terms of the FAR brings to notice that Cuckoo-ID placed in the second-lowest FAR (0.09%). Thus, the results of the performance comparison (summarized by Table III, and depicted in Fig. 5) reinforce the researcher’s former conclusion (drawn from Table II and Fig. 3, Fig. 4 and Fig. 5) that the IDS proposed in this study has profoundly good performance and is quite promising as an IDS that could replace the IDSs included in the comparisons in this paper (Table II and Table III).

In other respects, the comparison between the IDSs listed in Table II and those listed in Table III underlines that, in general, the IDSs employing feature selection methods have superior performance, in terms of the DR, than do those systems which use all of the features in the KDD’99 dataset without performing feature selection. The same holds almost as true with regard to the FAR in Fig. 4, where the IDSs employing feature selection methods (Table II) generally have much lower FARs than do those IDSs which do not apply feature selection (Table III). Therefore, the researcher recommends the use of IDSs with feature selection.

Fig. 4. A Comparison in Detection Rates (DRs) between Cuckoo-ID and IDSs that used All Features of the KDD’99 Dataset.

Fig. 5. A Comparison of FAR between Cuckoo-ID and IDSs that used All Features of the KDD’99 Dataset.

In view of the study’s findings, the researcher maintains that it will be quite interesting for future research to develop IDSs that will produce still higher DRs for all types of attacks. Moreover, different evolutionary algorithms are already known. The use of such algorithms can improve the DR of the entire system even if sometimes using all 41 features of the KDD’99 dataset without filtration. Furthermore, another type of dataset will be examined as UNSW-NB 15 to explore new types of attacks and to test the capability of Cuckoo-ID to detect new type of attacks that not included in KDD’99.

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