A hybrid two-step-model based on Cuckoo-Search and Grey Wolf Optimiser ensemble-based classifier approach for Network Intrusion Detection

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ABSTRACT

The new generation of Internet threats brought higher risks over network connectivity. This research suggests a layered feature selection Intrusion Detection System with an ensemble learning algorithms to enhance the decision about possible intrusion attacks. Cuckoo Search and Grey Wolf Optimiser approaches have been proposed to inherit their advantages to select the most distinctive features. The proposed classification model is combined with five classifiers, Fuzzy Unordered Rule Induction Algorithm, Voted Perceptron, Simple Logistic, Forest by Penalizing Attributes and C4.5 machine learning algorithms, to form a single voting-based ensemble classifier. The result indicated that the performance of the proposed ensemble based on the maximum of probabilities rule is better than the individual classifiers.

Key words: Machine Learning, Intrusion Detection Systems, Classification, Feature Selection, NSL-KDD.

I. INTRODUCTION

The massive evolution in information technology, Internet, computer networks and the widespread of Internet applications have brought much convenience to people's daily life and workplaces. Nonetheless, it borne a lot of security issues, such as vulnerabilities and virus attacks. Computer system security is defined as "the process of protecting confidentiality, integrity and availability" [1]. Intrusion Detection System (IDS) primary mission is to identify non-authorized accesses or intrusions, and suspicious activities or threats in information system or network [2]. It is responsible for monitoring all the activities in a system or network, to alert the system or network administrator whether a suspicious intrusion has occurred or not [3]. IDS can be classified into two broad categories according to the location in the network or by detection method, as illustrated in Figure 1. Based on the source of data IDS can be classified into Host-based and Network-based.

Host-Based: This IDS type acts on the client side by reviewing and detecting the important files and screening the usage of hardware resources [5]. Accordingly, it notifies the system administrator in case of any variation in the system or client files.

Network-Based: This type acts on the network side to monitor and inspect the unusual and abnormal traffic attack threats like the Denial of Services [6]. Yet, Network-Based IDS has very limited visibility inside the host machines.

Another categorization is based on the detection methodology, divide the IDS to signature-based IDS and anomaly-based IDS.

Signature-Based: It works by applying pattern matching to detect unknown attack patterns. So, it compares the incoming activity with the known attacks. In case if it recognizes any matching, it blocks the connection and stop it. Signature detection also refers misuse-based detection, pattern matching, rule-based detection [7].

Anomaly-Based: It recognizes the client or networking activities abnormal behaviour by applying several statistical, data-mining, learning based techniques [8]. This approach starts with creating a profile for the regular activities. To maintain the system security, it usually compares the new system activities with the collected profile. In case if an event did not match with the normal profile, this malicious behaviour will be considered as suspicious and it will raise an alarm.

Figure 1. Categories of IDS [4]

Due to high dimensionality of audit data produced during daily routine, existing IDS are unable to detect intrusion in real time, as it results in large computational. In an experiment conducted by MIT Lincoln Lab, to statistically analyse network traffic four giga bytes of compressed binary tcp-dump data, over 7 weeks were processed into five million connection records [9].

This indicates that the high dimensionality of the data under monitoring makes the analysis of IDS very challenging. One feasible approach to reduce the computation burden is to consider feature selection algorithms. Feature selection has a major role in detecting the most significant attributes and consequently improving classification results. This research is investigates applying a hybrid two-stage algorithm based on Grey Wolf Optimizer (GWO) and Cuckoo search algorithm to find the most optimal subset and removes low rank features.

This paper is organized as follows. After the introduction, Section 2 provides a review of the literature on using data mining algorithms with IDS. Section 3 describe the research methodology. Section 4 presents experimental results and discussion followed by the conclusion in Section 5.

II. RELATED WORK

Dorothy Denning implemented the first IDS in 1986 through applying statistical models on security incidents to identify any irregular or suspicious activities [10]. Since then, many researchers applied several machine learning algorithms to tackle it.

Alomari and Othman [11] proposed a wrapper-based feature selection approach using Artificial Bee Colony algorithm (ABC) as a search strategy and using Support Vector Machine (SVM) classifier. They conducted experiments using four random subsets of KDD CUP'99 dataset, wherein each subset approximately 4000 records. The evaluation criteria were calculated based on the balance between the average accuracy and the average accuracy of selected features. Experimental results showed that the ABC+SVM based wrapper approach achieved an overall accuracy of 99% with 8 features. Xingzhu in [12] proposed an Ant Colony Optimisation (ACO) and SVM feature weighting technique to address intrusion detection problem. Firstly, they built a complete fitness weighting index through utilising SVM grouping precision and highlighting subset measurements. Afterwards, they used the global and numerous exploration competences of ACO to construct the best solution feature list. The reported results showed that the suggested model succeeded in reducing the dimension of features with an accuracy rate of 95.75%.

Rani and Xavier proposed a signature-based IDS for zero-day attacks based on combining the C5.0 classifier and One Class SVM [13]. The original dataset was used to detect the outliers using a decision function during the training session. The experiments conducted using NSL-KDD Dataset showed that the approach reduced processing time, features and scored a detection rate of 99%.

Ghanem and Jantan developed an ABC and particle swarm optimisation (PSO) IDS with a feed-forward neural network [14]. The approach starts with generating the Pareto optimal solutions among a set of non-dominated solutions. Next, it uses the ABC+PSO to obtain the most significant features. Acharya and Singh introduced an unsupervised intelligent water drop (IWD) algorithm and SVM to classify KDD CUP'99 dataset [15]. Results showed that the proposed model (IWD+SVM) substantially helped in reducing the features from 41 to 9 with an accuracy rate of 99.09%. In the study of [16] a random forest model is proposed to detect various networking attacks on the NSL-KDD Dataset. In addition, the random forest classifier was associated with Gini feature importance for an explicit feature elimination. The experimental results showed that the proposed model achieved an accuracy of 99.88% with 25 features.

In the work of [17], a layered architecture selects the classifier based on attack type using NSL-KDD dataset. After data pre-processing, Cfs Subset Eval and Wrapper Subset Eval were applied with different classification algorithms to achieve high accuracy results in recognition all attack types. Another IDS model that is based on a hybrid feature selection and clustering is developed by [18]. The approach was based on combining K-Medoids clustering algorithm and SVM to select features. The proposed model is evaluated with KDD CUP'99 dataset using Naïve Bayes classifier. The results of the experiments indicated that the proposed approach scored an accuracy of 91.5% and detection rate of 90.1%.

Zhou and Cheng proposed an ensemble correlation-based Bat algorithm to solve intrusion detection problem [19]. Meanwhile, the ensemble classifier is built using C4.5, Random Forest and Forest by Penalizing Attributes (Forest PA) based on the average of probabilities rule. Experiments showed that the suggested approach recorded an accuracy result of 96.76% and a detection rate of 94.04%. A feature selection and clustering model for IDS based on decision tree classifier is implemented by combining filter and wrapper mechanism was developed by [20]. The wrapper method is based on linear correlation coefficient algorithm and the filter method applies

the cuttlefish algorithm. Results obtained over the KDD Cup'99 dataset indicated that the suggested model achieved an accuracy of 95.03% and a detection rate of 95.23%.

As most of the techniques in the literature try to tackle the IDS through applying data mining techniques, in this paper we suggest a combination of feature selection method (GWO+Cuckoo). The first phase tries to eliminate irrelevant features from the original dataset. While the second phase decreases the search range from the entire original feature space to the pre-selected features. This work aims to achieve higher accuracy rates compared to the literature works.

III. MATERIALS AND METHODS

a. NSL-KDD Dataset

NSL-KDD dataset is an enhanced version of the original KDD CUP'99 dataset which contains proportionate to 10% of the original dataset. It was proposed by [21] with removing redundant records and saving reasonable numbers of instances so that classifier doesn't show biased results. NSL-KDD dataset comprises of four components, KDDTrain+, KDDTest+, 20%KDDTraining+ and KDDTest-21[22].

For experimental purpose, we have used KDDTraining20% and KDDTest+ benchmark datasets to evaluate the proposed model which consists of 25,192 and 22,544 records respectively. Each record in dataset consists of 41 features labelled as normal or attack. Features are divided into four categories [22]: basic, content, time-based, and host-based features, as shown in Table 1. Even though the NSL-KDD dataset had a few issues, it is an extremely successful dataset that can be utilized for research purposes [23].

Table 1 List of features in the NSL-KDD data set [23]

Basic Features		Content Features		Time-Based Network Traffic Statistics		Host-based Network Traffic Statistics	
1.	Duration	10.	Hot	23.	count	32.	dst_host_serror_rate
2.	Protocol_type	11.	num_failed_logins	24.	srv_count	33.	dst_host_rerror_rate
3.	Service	12.	logged_in	25.	srv_serror_rate	34.	dst_host_same_src_port_rate
4.	Flag	13.	num_compromised	26.	srv_rerror_rate	35.	dst_host_srv_serror_rate
5.	Src_bytes	14.	root_shell	27.	rerror_rate	36.	dst_host_count
6.	Dst_bytes	15.	su_attempted	28.	serror_rate	37.	dst_host_srv_count
7.	land	16.	num_root	29.	same_srv_rate	38.	dst_host_diff_srv_rate
8.	Wrong_fragment	17.	num_file_creations	30.	diff_srv_rate	39.	dst_host_same_srv_rate
9.	urgent	18.	num_shells	31.	srv_diff_host_rate	40.	dst_host_srv_rerror_rate
		19.	num_access_files			41.	dst_host_srv_diff_host_rate
		20.	num_outbound_cmds				
		21.	is_host_login				
		22.	is_guest_login				

b. Methodology

The proposed approach is developed in four phases: data processing, feature selection, model selection, and model validation. The first phase includes data cleaning, standardization and normalization. Second phase suggests applying a hybrid algorithm based on GWO and Cuckoo search algorithm to find an optimal subset and removes low rank features. In the third stage, the data are divided into validation, training and test set. In the last phase, the performance of the selected model using the original and improved feature subset in combination with different ML classifiers is validated based on the maximum of probabilities rule. The overall framework is illustrated in Figure 2.

Figure 2. The Proposed Model for Feature Selection and Classification

a. Cuckoo Search via Lévy flights

Cuckoo search is a metaheuristic algorithm that has been extensively used in computational models and in adaptive search strategies for solving optimization problems [24]. One of the most desirable features of the Cuckoo search algorithm is computationally efficient and easy to implement with a smaller number of parameters [25].

The basic idea behind the Cuckoo search algorithm is derived from the breeding behaviour of some cuckoo species. These species choose to put eggs in a randomly chosen nests of other host birds, which have similar colour and pattern of the hosts' own eggs to reduce the probability of the hosts discovering them. The cuckoos rely on these host birds to accommodate their eggs. Sometimes, some of the host birds discover the foreign eggs and throw it away or simply leave their nests.

The Cuckoo search algorithm generates a new candidate solution (nest) $x_i^{(r+1)}$ for a cuckoo n [26,27]:

$$x_i^{(r+1)} = x_i^{(r)} + \alpha \otimes \text{Lévy}(\lambda) \quad 1$$

where s is the step size, and $\alpha > 0$ is the step size scaling. In most cases, α is set to 1. The symbol $\otimes$ is an entry-wise multiplication that is similar to those used in PSO algorithm. Basically, Lévy flights provide a random walk, while their random steps are drawn from a Lévy distribution for large steps:

$$\text{Lévy}(\lambda) \sim u = s^{-\lambda}, (1 < \lambda \leq 3) \quad 2$$

This makes the Cuckoo search more efficient in exploring the search space as it guaranteed that the algorithm will not fall into a local optimum trap [24].

b. Grey Wolf Optimization Algorithm

The GWO algorithm is a metaheuristic algorithm that was introduced by Mirjalili in 2014 [28]. The GWO algorithm is primarily motivated by the leadership and hunting behaviors of grey

wolves in nature, which mostly tend to live in packs consisting of 5-12 with strict hierarchy, and each wolf in the group has a defined role in the hunting process [29]. Each herd has four main ranks that are modeled as a pyramid [30]. The first level in the hierarchy of grey wolves is the leader of pack and is called alpha (α). This level is responsible for decisions about all wolf behaviors. Beta (β) wolves, is the second level and are responsible in helping in some choices in the packs. The third level is the delta (δ) wolves and are responsible for watching the boundaries of territory, protecting the group, hunting, and so on. The last level in the hierarchal model is called omega (ω), which is the weakest of the wolves, as it should obey other individuals' orders [29].

The second inspiration of GWO is the fact that wolves are known for their group-hunting strategy to catch prey. The hunting process starts with tracking and chasing the prey, then encircling and harassing until it finally stops moving before attacking in a manner that can be mathematically modeled as:

$$\vec{D} = |\vec{C} \cdot \vec{X}_p - \vec{X}(t)| \quad , \quad 3$$

$$\vec{X}(t+1) = |\vec{X}_p(t) - \vec{A} \cdot \vec{D}|$$

where $\vec{X}$ and $\vec{X}_p$ represent the positions of the prey and grey wolf at an iteration (t), respectively.

$\vec{A}$ and $\vec{C}$ are coefficient vectors that can be formulated as follows:

$$\vec{A} = |2a \cdot \overrightarrow{rand_1} - \vec{a}| \quad , \quad 4$$

$$\vec{C} = 2 \cdot \overrightarrow{rand_2}$$

where $\overrightarrow{rand_1}$ and $\overrightarrow{rand_2}$ are random vectors in [0,1]. $\vec{a}$ is linearly decreasing from 2 to zero over iterations as follows:

$$a = 2 - t * \frac{2}{iterations} \quad 5$$

The position of the grey wolf (X,Y) can be updated according to the position of the prey (X^*, Y^*).

The vectors $\vec{A}$ and $\vec{C}$ used to update the position of the best grey wolf. As the alpha, beta, and delta indicate the best three solutions, the rest of the wolves update their positions according to the best three solutions ($\vec{X}_1, \vec{X}_2$, and $\vec{X}_3$). This can be expressed as follows:

$$\vec{X}(t+1) = (\vec{X}_1 + \vec{X}_2 + \vec{X}_3)/3 \quad , \quad 6$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot (\vec{D}_\alpha) \cdot \vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}| \quad ,$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot (\vec{D}_\beta) \cdot \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}|,$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot (\vec{D}_\delta) \cdot \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}|$$

c. On Ensemble Classifiers

Ensemble learning is a paradigm applied in numerous classification problems where several individual classification base models are combined to obtain one decision. Ensemble methods' main objective is to achieve more accurate classification rates than a single model usually accomplishes [31]. Ensemble methods try to train multiple learning machines and combine their predictions to obtain better accuracy. This paradigm is powerful in achieving an estimation result with higher stability and accuracy by combining the decisions of multiple independent classification models [32]. As noticed in literature, several algorithms were chosen to build ensemble learning models, namely bagging, boosting, voting, Bayesian parameter averaging, and stacking [31,33].

For building classification learning model, we choose: Fuzzy Unordered Rule Induction Algorithm (FURIA), Voted Perceptron (VP), Simple Logistic (SL) and C4.5 machine learning

algorithms. Numerous studies have proven that decision trees are very effective methods of supervised learning [33]. C4.5 has been widely used in data mining due to its high efficiency in handling continuous, discrete attributes and missing values [34]. Meanwhile, RandomForest is generally simpler and can achieve accurate and robust results than single decision trees [35]. Moreover, ForestPA is a class implementing decision forest algorithm that generate trees with high precision based on the strength of the feature space. With its novel weight assignment strategy, bootstrap sampling, and penalized attributes, ForestPA generates highly diverse trees while retaining their higher individual accuracy [36]. FURIA classifier considered an extension of the RIPPER rule learning algorithm having its simplicity in generating unordered rule sets [37]. Moreover, it makes use of an efficient rule stretching method to deal with uncovered examples. VP is better in considering noisy or inseparable data as it approaches to small sample analysis and taking advantage of the boundary data of largest margin [38]. SL is a well-known discriminative technique for classification, which have been used in many applications [39,40].

IV. RESULTS AND DISCUSSION

Many scholars use accuracy and false positive rate, but others [41,42,43] claim that accuracy and false positive rates are not enough and merely using accuracy results can be misleading. We consider using Sensitivity, Specificity, Balanced Accuracy, Precision and *f*-measure as performance measurement metrics.

1. Data Pre-processing

Data pre-processing is a fundamental task in data mining and usually take place before constructing the training model to ensure the quality of the raw data. Data pre-processing procedure here involves raw data cleaning, standardization, and normalization.

a. Data Cleaning

Although NSL-KDD dataset has been improved, we noticed that the value of the feature “num_outbound_cmds” is always 0, so we decided to remove it.

b. Data Standardization

In data standardization we convert the symbolic features to numerical. The remaining 40 features, include 7 symbolic features and 33 numerical features. We started with “land”, “logged_in”, “is_hot_login”, and “is_guest_login” features which only contain “yes” and “no”, we encoded as 1 or 0. While the categorical features, “protocol_type”, “service”, and “flag”, which contain 3, 70, and 11 characters, respectively, one-hot encoding technique is applied.

c. Data Normalization

The main objective of data normalization is to decrease the numerical variations of different features, by scaling conditional feature value to a reasonable range. Here, we applied the Min-Max normalization map the initial features values *v* from the original [*min_A*, *max_A*] to [0, 1], and the normalized value *v'* is

$$v' = (v - \min_A) / (\max_A - \min_A) \quad 7$$

2. Discussion

Our procedure starts with first training the model using the KDDTrain+_20 dataset, once it is built the next step is to use the KDDTest+ dataset for testing the suggested model. Table 2 shows the first set of experimental results of all classifier with full set of features. It shows that the ensemble classifier model achieved superior result in terms of Specificity, classification accuracy and Precision rates as it achieved 82.7%, 91.4% and 78.3% respectively. Followed by the

ForestPA, which showed the second highest rates of accuracy, then the other classification algorithms.

Table 2. Full dataset-Comparative study of unprocessed dataset (with all the original features)

Model	<i>Sensitivity</i>	<i>Specificity</i>	<i>Balanced Accuracy</i>	<i>Precision</i>	<i>f-measure</i>
FURIA	0.706	0.713	0.857	0.765	0.734
VP	0.788	0.683	0.842	0.767	0.777
SL	0.784	0.688	0.844	0.769	0.776
ForestPA	0.540	0.771	0.885	0.757	0.630
C4.5	0.593	0.752	0.876	0.759	0.666
Ensemble	0.471	0.827	0.914	0.783	0.588

For the first feature selection phase, we applied the standard Cuckoo, PSO and Elephant search algorithms and select 13, 16 and 15 features respectively, among 41 features of NSL-KDD dataset. Table 3 lists the selected features with a number of selected features obtained by standard Cuckoo, PSO and Elephant search algorithms. From the table, it could be noted that the proposed Cuckoo algorithm performed the lowest number of features during the experiment runs followed by Elephant and PSO algorithms.

Table 3. Selected features in first step

Method	<i>No. Of Features</i>	<i>Selected Features</i>
Cuckoo	13	src_bytes dst_bytes wrong_fragment logged_in num_compromised serror_rate srv_serror_rate same_srv_rate diff_srv_rate srv_diff_host_rate dst_host_srv_diff_host_rate dst_host_srv_serror_rate flag
PSO	16	src_bytes dst_bytes land wrong_fragment logged_in num_root serror_rate srv_serror_rate same_srv_rate diff_srv_rate srv_diff_host_rate dst_host_same_srv_rate

		dst_host_srv_diff_host_rate dst_host_srv_serror_rate service flag
Elephant	15	src_bytes dst_bytes wrong_fragment logged_in num_shells count srv_serror_rate same_srv_rate diff_srv_rate dst_host_srv_count dst_host_srv_diff_host_rate dst_host_serror_rate dst_host_srv_serror_rate service flag

After constructing feature sets using various settings, either Cuckoo, PSO or Elephant these features were fed into individual and ensemble classifiers. Tables 4-6 present the result of classification performance of FURIA, VP, SL, ForestPA, C4.5 and the ensemble classifier over the obtained dataset from Cuckoo, PSO and Elephant search algorithms respectively. The highest Specificity, Balanced Accuracy and Precision readings were scored with the Cuckoo search algorithm with 13 features.

We also noticed that the ensemble classifier in all cases obtained the best results over individual classifiers in terms of Specificity, Balanced Accuracy and Precision. Up to this point, feature selection using Cuckoo search algorithm gives better result than other heuristic search algorithms. According to the Venn diagram analysis (Figure 2) showing that there are 10 common features between Cuckoo, PSO and Elephant metasearch. It includes: src_bytes, dst_bytes, wrong_fragment, logged_in, srv_serror_rate, same_srv_rate, diff_srv_rate, dst_host_srv_diff_host_rate, dst_host_srv_serror_rate and flag.

Table 4. Performance classification based on Cuckoo search in first step

Model	<i>Sensitivity</i>	<i>Specificity</i>	<i>Balanced Accuracy</i>	<i>Precision</i>	<i>f-measure</i>
FURIA	0.424	0.837	0.919	0.775	0.548
VP	0.490	0.818	0.909	0.780	0.602
SL	0.491	0.815	0.908	0.778	0.602
ForestPA	0.507	0.791	0.896	0.763	0.609
C4.5	0.478	0.825	0.912	0.783	0.594
Ensemble	0.407	0.849	0.925	0.781	0.535

Table 5. Performance classification based on PSO search in first step

Model	<i>Sensitivity</i>	<i>Specificity</i>	<i>Balanced Accuracy</i>	<i>Precision</i>	<i>f-measure</i>
FURIA	0.576	0.787	0.893	0.781	0.663
VP	0.505	0.813	0.907	0.782	0.614
SL	0.509	0.810	0.905	0.780	0.616
ForestPA	0.588	0.782	0.891	0.781	0.671
C4.5	0.584	0.782	0.891	0.779	0.668
Ensemble	0.501	0.819	0.910	0.786	0.612

Table 6. Performance classification based on Elephant search in first step

Model	<i>Sensitivity</i>	<i>Specificity</i>	<i>Balanced Accuracy</i>	<i>Precision</i>	<i>f-measure</i>
FURIA	0.510	0.812	0.906	0.782	0.617
VP	0.494	0.786	0.893	0.753	0.597
SL	0.495	0.786	0.893	0.753	0.598
ForestPA	0.539	0.801	0.900	0.782	0.638
C4.5	0.528	0.807	0.904	0.784	0.631
Ensemble	0.462	0.835	0.917	0.787	0.582

Figure 2. Venn diagram analysis of shared features between Cuckoo, PSO and Elephant search technique

In the second phase, we applied the GWO algorithm over the reduced set of features. Tables 7 and 8 list the obtained features and the classifier's performance. Worth noting that the obtained features were among the previously mentioned common feature. The ensemble classifier obtained the best results over individual classifiers in terms of Specificity, Balanced Accuracy and Precision where it scored 83.5%, 91.8% and 78.3% respectively with 8 features.

Table 9 shows the summary of result pointing to the average and worst classification rates with the number of selected features for NSL-KDD. From the Table, we noticed that the proposed

Cuckoo+GWO algorithm achieved the second highest result for best average accuracy compared to the other heuristic search algorithms. Besides that, the proposed algorithm was superior from the other techniques in the accuracy of worst classification and the number of chosen features. So, as the proposed algorithm worked on a smaller number of features compared to the original dataset, it is obvious that it was efficient enough to maintain a fair performance. Table 10 illustrates the comparison of our proposed approach with other approaches. Obviously, the proposed algorithm obtained significant result compared to approaches in literature in terms of classification accuracy and number of selected features.

Table 7. Selected features based on Cuckoo+GWO in second step

Method	No. Of Features	Selected Features
Cuckoo+GWO	8	dst_bytes wrong_fragment logged_in srv_serror_rate same_srv_rate diff_srv_rate dst_host_srv_diff_host_rate flag

Table8. Performance classification based on Cuckoo+GWO in second step

Model	Sensitivity	Specificity	Balanced Accuracy	Precision	f-measure
FURIA	0.524	0.789	0.895	0.767	0.623
VP	0.459	0.828	0.914	0.779	0.577
SL	0.464	0.826	0.913	0.778	0.581
ForestPA	0.527	0.770	0.885	0.752	0.620
C4.5	0.451	0.835	0.917	0.783	0.572
Ensemble	0.450	0.835	0.918	0.783	0.571

Table9: Summary of average and worst classification rates

Method	Average classification Accuracy	Worst classification Accuracy	Selected Features
None	0.870	0.842	40
Cuckoo	0.912	0.896	13
PSO	0.902	0.893	16
Elephant	0.902	0.893	15
Cuckoo+GWO	0.907	0.885	8

Table10. Comparison of Cuckoo+GWO-ensemble and previous research results (accuracy in %)

Author and Year	Feature Selection Algorithm	Dataset	Classification Algorithm	Classification Accuracy	No. Of Selected Features
Our proposed approach	Cuckoo+GWO	NSL–KDD	Ensemble classifier	91.8%	8
Keshtgary, Rikhtegar et al., 2018 [18]	K-Medoids+SVM	KDD CUP’99	Naïve Bayes classifier	91.5%	10
Zhou and Cheng (2019) [19]	Correlation-based+ Bat-Algorithm	NSL–KDD	C4.5, Random Forest (RF) and ForestPA	96.76%	10
Mohammadi et al., 2019 [20]	linear correlation coefficient + cuttlefish algorithm	KDD CUP’99	Decision tree	95.03%	10
Negandhi et al. 2019 [16]	Gini feature importance	NSL–KDD	random forest	99.88%	25

CONCLUSION

In this research we suggested a layered feature selection IDS with an ensemble learning algorithms to enhance the decision about possible intrusion attacks. We reduced the dimensions of the NSL-KDD dataset by using two-stage feature selection technique. Cuckoo and GWO approaches have been propose to classify network traffic, whether normal or attack. The proposed classification model was boosted by introducing ensemble learning of FURI, VP, SL, ForestPA and C4.5 machine learning algorithms. With this research topic, we managed to get good results by using ensemble learning.

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