An Efficient Network Intrusion Detection System Based on Feature Selection and Ensemble Classifier

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ABSTRACT
Since Internet is so popular and prevailing in human life, countering cyber threats, especially attack detection, is a challenging area of research in the field of cyber security. Intrusion detection systems (IDSs) are essential entities in a network topology aiming to safeguard the integrity and availability of sensitive assets in the protected systems. Although many supervised and unsupervised learning approaches from the field of machine learning and pattern recognition have been used to increase the efficacy of IDSs, it is still a problem to deal with lots of redundant and irrelevant features in high-dimension datasets for network anomaly detection. To this end, we propose a novel methodology combining the benefits of correlation-based feature selection (CFS) and bat algorithm (BA) with an ensemble classifier based on C4.5, Random Forest (RF), and Forest by Penalizing Attributes (Forest PA), which can be able to classify both common and rare types of attacks with high accuracy and efficiency. The experimental results, using a novel intrusion detection dataset, namely CIC-IDS2017, reveal that our CFS-BA Ensemble method is able to contribute more critical features and significantly outperforms individual approaches, achieving high accuracy and low false alarm rate. Moreover, compared with the majority of the existing state-of-the-art and legacy techniques, our approach exhibits better performance under several classification metrics in the context of classification accuracy, f-measure, attack detection rate, and false alarm rate.

CCS CONCEPTS
• Security and privacy → Intrusion detection systems; • Information systems → Data mining; • Computing methodologies → Machine learning;

KEYWORDS
Cyber security; Intrusion detection system; Data mining; Feature selection; Ensemble classifier

1 INTRODUCTION
Nowadays, the applications of the Internet help society in many areas such as electronic communication, teaching, commerce and entertainment, it has become a part of daily life of the people. However, cyber security has become vulnerable due to the massive expansion of the computer networks and rapid emergence of the hacking tools and intrusion incidents. The necessity of developing cyber security has, therefore, attracted considerable attention from industry and academia around the world. Despite the use of different security applications, such as firewalls, malware prevention, data encryption, and user authentication, many organizations and enterprises fall victims of contemporary cyber-attacks[1]. In order to sneak into the system, attackers might deliberately exploit the vulnerabilities of the target cyber system and launch different types of attacks, which may lead to the leakage or damage of private information from organizations and enterprises.

As technology is rolling out these attacks make cyber security more vulnerable and therefore intrusion detection systems (IDSs) is introduced to eliminate these threats. IDSs are assigned to protect systems from a variety of attacks threatening their confidentiality, integrity and availability. To be more specific, IDSs are widely deployed in various distributed systems, perceiving the malicious intrusions of a host or a network and taking rapid countermeasures to prevent further infections and spread. In general, IDSs are classified into two major categories based on detection mechanisms; anomaly and misuse detection[2]. Anomaly detection is designed to detect malicious actions through identifying deviations from a normal profile behavior. Even though this kind of IDSs perform better in detecting novel attacks, they usually suffer from a high False Positive (FP) rate[3]. Misuse detection, where the detection process is based on known signatures or patterns, aims to distinguish legitimate instances from the malicious ones. Without the drawback of anomaly detection, misuse detection is reliable for detecting known attacks with low FP rate. Nevertheless, this kind of IDSs cannot identify unknown attacks or variations of known ones.

As the attackers become more sophisticated, new threats and vulnerabilities emerge and evolve rapidly. On one hand, the risk for critical infrastructures to be compromised significantly increases in short order, and, to detect and deal with novel attacks, a higher requirement for IDS has also been brought forward on the other hand. Hence, many approaches have been researched and developed to improve the detection rate and performance of IDSs; one of them is Machine learning (ML)[4], which can be applied for both anomaly and misuse detection models. By analyzing network traffic passing through central network nodes, an IDS not only need to distinguish between benign and malicious traffic, but also infer the specific class of an attack occurring in the protected system. Moreover, only a fraction of the traffic may indicate malicious behaviors while a network is flooded with normal traffic flows, which lead to the difficulty of identifying attacks with high Attack Detection Rate (ADR) while keeping the False Alarm Rate (FAR) low. In addition,
the numerous attack types and network traffic attributes pose a significant challenge for ML as they expand the search space of the problem and lead to high computational and time complexity.

In this paper, we propose a novel network intrusion detection system to detect various types of attacks with high accuracy and efficiency. Our solution utilizes ensemble classifier blended with nature-inspired metaheuristic optimization algorithm in order to reduce the bias and variance among different training datasets and select the right feature subset for accurate intrusion detection. On the one hand, to overcome the problem of class imbalance, decisions from multiple classifiers are combined into one using an ensemble approach based on a vote classification. On the other hand, as a means of dimensionality reduction and redundancy elimination, feature selection based on nature-inspired metaheuristic optimization algorithm is used to retrieve a subset of the original features to eliminate irrelevant features and retain the most related features. In this way, computational and time complexity can be reduced and an accurate and unbiased model can be generated to detect both popular and rare intrusive events. The major contributions of our work are summarized as follows:

- We propose a novel methodology that combines the benefits of feature selection and ensemble classifier with the aim of providing efficient and accurate intrusion detection.

- In the context of feature selection, Correlation-based Feature Selection(CFS) and a nature-inspired algorithm called Bat Algorithm(BA) were utilized to reduce irrelevant features.

- An ensemble approach was used to improve the predictive performance by combining decisions from multiple classifiers (C4.5, RF, and Forest PA) into one based on the average of probabilities (AOP) combination rule.

- The proposal is compared with other state-of-the-art and legacy machine learning proposals in a novel intrusion detection dataset, namely CIC-IDS2017, which includes many types of novel attacks and high-dimensionality features.

The rest of the paper is organized as follows: In Section 2, we review the background information concerning the IDSs and state our goals. The proposed methodology is given in Section 3, while in Section 4 we provide the evaluation results and a comparative analysis is performed of our proposal relative to the existing state-of-the-art and legacy techniques. Finally, the conclusion is presented in Section 5.

2 RELATED WORK

For purpose of reducing computational complexity, the technique of feature selection[5] can be used as a pre-processing step in a machine learning algorithm to eliminate irrelevant features and retain the most related features while preserving or even enhancing the total performance of the system. Feature selection, which can be used to retrieve a subset of the original features without alteration, is typically classified into three categories: filter, wrapper, and embedded methods[6]. Moreover, the combination of different base machine learning algorithms is called as ensemble method, such as Bagging, Boosting and Stacking. In literature survey, it is found that an ensemble method of machine learning helps to reduce false positive rates.

Recently, Many IDSs have been proposed using feature selection and ensemble method to improve accuracy for classification. Hota and Shrivas, 2014[7], proposed a model that used different feature selection techniques to remove the irrelevant features in the dataset and developed a classifier that is more robust and effective. The results showed that C4.5 with Info Gain had better results and achieved highest accuracy of 99.68% with only 17 features. In 2015, Malik et al.[8] proposed the combination of Particle Swarm Optimization (PSO) and Random Forest (RF). More appropriate features for each class helps the proposed model produce a higher accuracy along with low false positive rate in classification compared with other algorithms. Paulauskas and Auskalnis, 2017[9], proposed an ensemble model of four different classifiers: J48, C5.0, Naive Bayes and PART, that are depend on the idea of combining multiple weaker learners to create a stronger one. Their results showed that their ensemble model produces more accurate results for an IDS. Khammassi and Krichen, 2017[10] have applied a wrapper methods based on a genetic algorithm as a search strategy and logistic regression as a learning algorithm for network IDSs to choice the best subset of features. The result showed that their method provided high detection rate with a subset of only 18 features for the KDD99 dataset and 20 features for the UNSW-NB15 dataset. In 2018, Abdullah et al.[11] proposed a framework of intrusion detection with selection of features in the NSL-KDD dataset that based on dividing the input dataset into different subsets according to each attack. The optimal features set is generated by combining the list of subsets that obtained using information gain filter. The experiment result showed that the highest accuracy obtained when using Random Forest and PART classifiers under combination methods namely the product probability rule.

From this inspiration, we are trying to integrating feature selection with an ensemble classifier for an efficient and accurate IDS. In this work, researchers will try to conduct some experiments to differentiate and discover the normal and abnormal behavior. To make comparison with some of the legacy and state-of-the-art methods, the proposed IDS methodology was evaluated based on a novel intrusion detection dataset, namely CIC-IDS2017, which includes many types of novel attacks and high-dimensionality features.

3 PROPOSED METHODOLOGY

In this paper, the proposed methodology using CFS and BA with ensemble classifier based on C4.5, RF, and Forest PA algorithms is presented to enhance the classification ability of the end model. Fig.1 demonstrates the detection framework of the proposed method, which consists of three stages including: feature selection, build and train the ensemble classifier, and attack recognition. In order to overcome the problem of class imbalance, feature selection based on CFS and BA is used to determine a subset of the original features to eliminate irrelevant features. The ensemble classifier was chosen after extensive experimentation of assembling various learning methods, including C4.5, RF, and Forest PA to detect both popular and rare intrusive events. The ensemble of C4.5, RF, and Forest PA achieved the best performance in terms of classification accuracies. Moreover, voting technique was used to combine the probability distributions of the base learners for better performance in terms of
classification accuracies. Detailed information about the framework is provided in Sections 3.1–3.2.

3.1 Feature selection

The aim of feature selection is to find a subset of the attributes from the original set which are representative enough for the data, and the attributes in the subset are highly relevant to the prediction. Feature selection approaches can be mainly categorized into wrapper, filter and embedded approaches. While filter approaches assess the relevance of the features from the dataset and the selection of the features is based on validation, the classification performance is used in wrapper approaches as part of the feature subsets evaluation and selection processes. In contrast to wrapper approaches, embedded approaches are computationally less intensive than wrappers because they incorporate an interaction between feature selection and learning process. Although embedded approaches integrate a regularized risk function to optimize the features designating parameters and the predictor parameters[12], the redundancy of the selected feature subset which is searched in the selection process and enhance the accuracy of the classification.

CFS with BA is proposed to optimize the efficiency of the feature selection process. Feature selection approaches can be mainly categorized into redundant and irrelevant attributes[14]. Redundant and irrelevant features are those that are highly correlated with each other. While insignificant features that show low association with the class but uncorrelated with each other. The feature subset assessment function to form the fitness functions and evaluation of the selected feature subset. CFS-BA approach utilizes correlation based correlation and average inter-correlation among features by using Eq.1. As one of classical filter algorithms, CFS can easily select the redundant features and reduce the redundancy of the selected feature subset which is searched in the search space for the optimal solution.

3.1.1 Correlation-based feature selection(CFS). CFS[16] is one of classical filter algorithms that choose features according to the result of heuristic (correlation-based) assessment function. The preference of this function is to select subsets whose features are extraordinarily related with the class but uncorrelated with each other. While insignificant features that show low association with the class ought to be ignored on the grounds, repetitious features are chosen due to high relation with at least one of the rest of features. The acknowledgment of a feature will rely upon the degree to which it predicts classes in the instance space not as of now anticipated by different features. The feature subset assessment function[17] in CFS is as:

$$M_s = \frac{k \tau_{cf}}{\sqrt{k + k(k - 1) + \tau_{ff}}}$$  (1)

In Eq.1, $M_s$ is the heuristic evaluation for a feature subset s including k features, $\tau_{cf}$ is the mean correlation degree between features and the category label, and $\tau_{ff}$ is the average inter-correlation degree among features. The evaluation of CFS is a method of correlation based on feature subsets. A bigger $\tau_{cf}$ or smaller $\tau_{ff}$ in acquired subsets by the method produce a higher evaluation value, and the set of features with the highest value found during the process is utilized to reduce the size of both the training and testing set.

3.1.2 Bat algorithm(BA). The original bat algorithm was developed by Xin-She Yang in 2010[18, 19]. The main inspirations for these works were the echolocation behavior of microbats. As BA uses frequency tuning, it is in fact the first algorithm of its kind in the context of optimization and computational intelligence. Each bat flies randomly with a velocity $v_i^t$, a location $x_i^t$, and a frequency $f_i$ at iteration $t$, in a $d$-dimensional search or solution space. The location can be considered as a solution vector to a problem of interest. Among the n bats in the population, the current best solution $x_s$, found so far can be archived during the iterative search process.

Defined by Yang on the paper[20], the updating rules for the location $x_i^t$ and velocity $v_i^t$ at time step $t$ are given by

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta$$  (2)

$$v_i^t = v_i^{t-1} + (x_i^{t-1} - x_s)f_i$$  (3)

$$x_i^t = x_i^{t-1} + v_i^t$$  (4)

where $\beta \in [0,1]$ is a random vector drawn from a uniform distribution.

For the local search part, once a solution is selected among the current best solutions, a new solution for each bat is generated locally using random walk

$$x_{new} = x_{old} + eA^t$$  (5)

where $e$ is a random vector drawn from a uniform distribution in [-1,1] or a Gaussian distribution, while $A^t$ is the average loudness of all the bats at this time step.

In addition, the loudness $A_i^t$ and the rate $r_i^t$ of pulse emission have to be updated accordingly as the iterations proceed. The updating rules for them can be written as

$$A_i^{t+1} = \alpha A_i^t$$  (6)

$$r_i^{t+1} = r_i^0(1 - e^{-\gamma t})$$  (7)

where $0 < \alpha < 1$ and $\gamma > 0$ are constants.

3.1.3 Proposed CFS-BA approach for feature selection. In this section, we proposed CFS-BA based feature selection approach, which is used to assess the importance and the dismissal of the selected feature subset. CFS-BA approach utilizes correlation based feature technique to form the fitness functions and evaluation of the integration of the reduced feature subset. For a feature subset $S$ with $k$ features, $S = (s_1, s_2, ... s_k)$, CFS assesses the mean feature-class correlation and average inter-correlation among features by using Eq.1. As one of classical filter algorithms, CFS can easily select the subset of independently good features according to the result of correlation-based evaluation function. However, this feature subset may not be the best combination because of redundancy between features. To remove the redundant features and reduce the dimensionality, BA, which inspired by the echolocation behavior of microbats, was introduced. In BA, every solution of the problem is denoted by the location of a bat, which can be represented by a vector. Bats fly in the search space to search for the best solutions and during this movement, the current best solution found so far can be archived. The population scans for the ideal arrangement by refreshing and updating the position of every bat based on Eq.2–Eq.4 during the iterative search process.
The feature selection process of the CFS-BA approach is presented in Algorithm 1. The main parts of the CFS-BA algorithm can be summarized as follows:

**Algorithm 1 CFS-BA approach for feature selection**

**Input:** Training Dataset and Testing Dataset

**Output:** Selected Feature Subset

1: Initialize a population of \( n \) bats \( X_i = (x_{i1}, ..., x_{iD}) \) \((i = 1, 2, ..., n)\) and \( v_i \)
2: Initialize frequency \( f_i \), pulse emission rate \( r_i^f \) and loudness \( A_i^f \)
3: Initialize \( f_i(X_i) \) (cf. Eq.1) and \( X_{best} \)
4: Initialize \( f_{temp}(i) \) and \( X_{temp}(i) \) for solution storage
5: \( \text{while } 1 \leq t \leq \text{Max no. of iterations} \) do
6: \( \text{for } i = 1 \text{ to } n \) do
7: \( \text{Generate new } f_i \) (cf. Eq.2)
8: \( \text{Update } X_i \text{ and } v_i \) (cf. Eq.3 and Eq.4)
9: \( \text{if } r_i^f < \text{rand}(0,1) \text{ then } \)
10: \( \text{Select a } X_i \text{ from } X_{best} \)
11: \( \text{Generate a new } X_{new} \) (cf. Eq.5)
12: \( \text{end if} \)
13: \( \text{Calculate } f_{new}(X_{new}) \) (cf. Eq.1)
14: \( \text{if } f_{new}(X_{new}) \leq f_{temp}(i) \text{ and } N(0,1) < A_i^f \text{ then } \)
15: \( f_{temp}(i) \leftarrow f_{new}(X_{new}) \)
16: \( X_{temp}(i) \leftarrow X_{new} \)
17: \( \text{Decr \( A_i^f \) and Inc \( r_i^f \) (cf. Eq.6 and Eq.7)} \)
18: \( \text{end if} \)
19: \( \text{if } f_{temp}(i) \geq f_{new}(X_{new}) \text{ then } \)
20: \( X_{best} \leftarrow X_{new} \)
21: \( \text{end if} \)
22: \( \text{end for} \)
23: \( t = t + 1 \)
24: \( \text{end while} \)

- Initialization (lines 1-4). The parameters of algorithm, generation and evaluation of the initial population are initialized here.
- New solution generation (lines 7-8). Here, bats in the population are moved in the search space according to updating rules of Eq.2–Eq.4.
- Local search process (lines 9-11). We select a solution among the best solutions, then generate a local solution around the selected one by random walks.
- Evaluation of the new solution (line 13). The feature subset assessment function in CFS is utilized here to evaluate the new solution.
- Archive of the new solution (line 14-17). The new solution which meets our requirement needs to be archived here. After that, the loudness \( A_i^f \) and the rate \( r_i^f \) of pulse emission have to be updated using Eq.6–Eq.7.
- Update of the best solution (line 19-20). We compare the evaluation result of the archived solution and find the current best \( X_{best} \) until the iterations end.

### 3.2 Ensemble classification

The ensemble classification methods usually combine multiple diverse, unstable and good classifiers in some way[21]. These classifiers are powerful to solve the same problem and collectively achieve a forecasting result with higher stability and accuracy by creating multiple independent models and combining them[22]. The classical scenarios for employing ensemble classifiers are representational issue, statistical reason, and computational reason [30]. For the first scenario, sometimes a single classifier is not qualified to find the best representation in the hypothesis space. For the second scenario, a single classifier may lead to a weak result when the input dataset is not sufficient to train the learning algorithm. For the last case, an issue can occur when it is too computationally time consuming for an individual classifier to produce a suitable hypothesis.

Bagging[23] and Boosting[24] are the two most popular algorithms in ensemble learning, usually producing good results in classification and being widely chosen to build many ensemble models.
models. Moreover, the other well-known ensemble learning methods for improving the performance of classification are Voting[25], Bayesian parameter averaging[26], and Stacking[27]. Likewise, ensemble methods have been shown to improve accuracy in many use cases, including intrusion detection. For security professionals, ensemble classifiers provide mechanisms that aid in analysis such as similarity to existing known malicious or benign samples. In this study, an ensemble classifier consists of three different decision tree classifiers, namely C4.5, RF, and Forest PA, is proposed to improve the predictive performance of IDS. These classifiers were used in a vote algorithm and based on the average of probabilities (AOP) combination rule.

3.2.1 C4.5. C4.5[28] is a typical decision tree algorithm which is developed based on the ID3[29] algorithm. This algorithm passes through decision tree, visits each node and select optimal split based on the maximisation of the gain ratio, which is represented by the following formula:

$$\text{GainRatio}(A) = \frac{\text{Gain}(A)}{\text{SplitInfo}(A)}$$  \hspace{1cm} (8)

In the process, an attribute with the highest information gain is chosen as splitting attribute for the node $N$. Information gain represents how much uncertainty in the set $D$ is reduced after it is partitioned on attribute $A$. The uncertainty in the data set $D$ is measured by entropy. This can be calculated as:

$$\text{Entropy}(D) = -\sum_{x \in X} p(x)\log_2 p(x)$$ \hspace{1cm} (9)

where $X$ is the set of classes in $D$ and $p(x)$ is the proportion of number of elements in class $x$ to the number of elements in set $D$.

Likewise, $\text{SplitInfo}$ is the term which describes how equally the attribute splits the data and can be calculated as:

$$\text{SplitInfo}(A) = -\sum_{j=1}^{n} \left( \frac{|D_j|}{|D|} \right) \log_2 \left( \frac{|D_j|}{|D|} \right)$$ \hspace{1cm} (10)

where $|D_j|$ represents the weight of $j$-th partition in the set $D$.

Moreover, as an improvement of ID3 algorithm, C4.5 has the capability to model or classify both discrete and continuous attributes, and can ignore missing attribute values in a dataset.

3.2.2 Random Forest(RF). Random Forest, proposed by Breiman in [30], is another decision tree technique that operates by constructing multiple decision trees. It takes thousands of input variables without variable deletion and classifies them based on their significance. RF can be described as an ensemble of classification trees where every tree contributes with a single vote for the task of the most frequent class to the input data. Compared to other machine learning methods (e.g., support vector machine, artificial neural network), there are fewer parameters to be specified when running Random Forest. In RF, a collection of individual tree structured classifiers can be defined as:

$$\{ h(x, \theta_k), k = 1, 2, ..., i \cdots \}$$ \hspace{1cm} (11)

where $h$ represents Random Forest classifier, $(\theta_k)$ stands for random vectors distributed independently identical and each tree has a vote for the most famous class at input variable $x$. The nature and dimensionality of $\theta$ depends on its use in tree construction.

The key to the success of RF is the creation of each decision tree that makes up the forest. A bootstrapped subset of the training dataset is created to train each tree in the forest. Due to this fact, on average, each tree makes use of around two-thirds of the training dataset. The unused elements are called by the Out Of Bag (OOB) samples, which are used for inner cross-validation to evaluate the classification accuracy of RF. Moreover, Random Forest has a low computational burden, and it is insensitive to the parameters and outliers. Besides, over-fitting is less of an issue compared to individual decision tree and there is no need to prune the trees which is a cumbersome task[31].

3.2.3 Forest by Penalizing Attributes(Forest PA). Unlike some existing algorithms that use a subset of the non-class attributes, Forest PA[32] is an algorithm that builds a set of highly accurate decision trees by exploiting the strength of all non-class attributes available in a data set. At the same time, some weight-related concerns, such as weight assignment strategy and weight increment strategy, are taken into account in order to retain individually accurate and promote strong diversity.

For the weights of the attributes that appear in the latest tree, Forest PA will randomly update the weights for those attributes within a Weight-Range(WR), which can be defined as follows:

$$\text{WR}^d = \begin{cases} [0.0000, e^{-\frac{\lambda}{\sigma}}], & \lambda = 1 \\ [e^{-\frac{\lambda}{\sigma}} + \rho, e^{\frac{\lambda}{\sigma}}], & \lambda > 1 \end{cases}$$ \hspace{1cm} (12)

where $\lambda$ represents the level of the attribute and $\rho$ is used to ensure the WR for different levels be non-overlapping. For example, if an attribute appears in the root node then its $\lambda = 1$. In the same way, if an attribute is tested at a child node of the root node then its $\lambda = 2$.

Moreover, to address the negative effect of retaining weights which are not present in the latest tree, Forest PA has a mechanism to gradually increase weights of the attributes that have not been tested in the subsequent trees. Let an attribute $A_j$ is tested at Level $\rho$ of the $t_j-1$-th tree with $\eta$ height and its weight is $\omega_i$. Then, the weight increment value $\sigma_i$ of $A_j$ is calculated as:

$$\sigma_i = \frac{1.0 - \omega_i}{(\eta + 1) - \lambda}$$ \hspace{1cm} (13)

3.2.4 Vote. Vote is a meta algorithm which performs the decision process by applying several classifiers[33]. It uses the power of several individual classifiers and applies a combination rule for the decision. For example, minimum probability, maximum probability, majority voting, product of probabilities, and average of probabilities are different examples for combination rules. In average of probabilities approach[34], the class label is determined based on the maximum value of the average of predicted probabilities.

Suppose we have $l$ classifiers $C = \{C_1, ..., C_l\}$, and $c$ classes $\Omega = \{\omega_1, ..., \omega_c\}$. In this paper, for the dataset considered in our experiment, $c = 15$, and $l = 3$ as listed above. A classifier $C_l : R^n \rightarrow \{0, 1\}^c$ accepts an object $x \in R^n$ and outputs a vector $[P_{c_l}(\omega_1|x), ..., P_{c_l}(\omega_c|x)]$, where $P_{c_l}(\omega_j|x)$ denotes the probability assigned by the classifier $C_l$ that object $x$ belongs to class $\omega_j$. For
each class \(\omega_j\), let \(m_j\) represents the mean of the probabilities assigned by the \(l\) classifiers, which can be calculated as:

\[
m_j = \frac{1}{l} \sum_{i=1}^{l} P_c(\omega_j|x)
\]  

(14)

Let \(M = [m_1, ..., m_c]\) be the set of mean probabilities for \(c\) classes. Then, \(x\) is assigned to the class \(\omega_k\) if \(m_k\) is the maximum in \(M\).

4 EVALUATIONS AND RESULTS

As stated before, this paper aims to develop an efficient intrusion detection method with high accuracy and low false alarms. For this purpose, a hybrid method, combined CFS and BA named CFS-BA, was performed to determine the irrelevant features in order to eliminate the irrelevant features, as well as to improve the classification efficiency. In the classification step, an ensemble classifier combined three different algorithms, C4.5, RF, and Forest PA based on the AOP combination rule, was trained and tested based on the CIC-IDS2017 dataset. Results show that the CFS-BA with ensemble classifier outperformed every single other classifier by achieving high classification performance results. The experiments were performed by Weka 3.8.3 [35] on desktop PC with 3.6 GHz Intel Core i7-4790 processor and 16GB RAM.

4.1 The CIC-IDS2017 dataset

During the evaluation of IDS, one of the challenges faced by researchers is finding a suitable dataset. Acquiring a real world dataset that represents the traffic flowing through the network without any sort of anonymization or modification is a problem that has been continuously encountered by the cybersecurity research community [36]. Even in the cases where the data is allowed to be released or shared for public use, it will be heavily anonymized or severely altered. This will cause a lot of the essential data components that are considered critical to the researchers to be lost or no longer reliable. For this reason, many researchers have decided to use simulated data sets like the well-known KDD99 dataset [37], or one of its contemporaries the NSL-KDD [38]. Recently there has been a significant effort to try and develop data sets that are reflective of real world data.

The Canadian Institute for Cybersecurity (CIC) published an intrusion detection dataset named CIC-IDS2017 [39] in 2017. This dataset contains benign and the most up-to-date common attacks, which resembles the true real-world data packet capture (PCAPs). It also includes the results of the network traffic analysis using CICFlowMeter with labeled flows based on the time stamp, source and destination IPs, source and destination ports, protocols and attacks (CSV files). This is one of the newest labeled intrusion detection dataset, which covers all the eleven necessary criteria with common updated attacks such as DDoS, Brute Force, XSS, SQL Injection, Infiltration, Port Scan and Botnet.

Therefore, in our experiments, we use CIC-IDS 2017, which contains 2,830,743 records devised on 8 files, each record having 78 features. Each record of CIC-IDS 2017 is labelled as Benign or one of fourteen type of attacks.

4.2 Dataset preprocessing

Data preprocessing is the most time consuming and essential step in data mining. Realistic data typically comes from heterogeneous platforms and can be noisy, redundant, incomplete, and inconsistent [40]. Thus, it is important to transform raw data into a format suitable for analysis and knowledge discovery. In this research, the preprocessing step involves removing outliers and redundant instances, as well as data transforming.

4.2.1 Data filtration. Due to the heterogeneity of the platforms, the raw data in CIC-IDS2017 will inevitably contain anomalous and redundant instances, which may have a negative influence on classification accuracy. In order to solve this problem, these instances need to be removed from the dataset at the beginning of our experiments. To be more specific, we concatenate the 8 files in one same table and remove all records that have the feature qisFlow Packets/ąś equal to ‘Infinity’ or ‘NaN’. Then, we remove 8 features which have the same value for all records, namely Bwd PSH Flags, Bwd URG Flags, Fwd Avg Bytes/Bulk, Fwd Avg Packets/Bulk, Fwd Avg Bulk Rate, Bwd Avg Bytes/Bulk, Bwd Avg Packets/Bulk and Bwd Avg Bulk Rate. The utilized dataset contains 2,827,876 records with each record having 70 features after screening.

4.2.2 Data normalization. Different scales among features can degrade the classification performance, for example, features that take on large numeric values, e.g., ‘Flow Duration’ can dominate the classifier’s model relative to features with relatively small numeric values such as ‘Total Fwd Packets’. Accordingly, normalization is a ‘scaling down’ transformation which maps features onto a normalized range. A simple and fast approach called minimum-maximum method was used in our experiments, which can be defined as:

\[
\tilde{x} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}
\]  

(15)

where \(x_{\text{min}}\) and \(x_{\text{max}}\) are the minimum and maximum values of feature \(x\).

4.2.3 Creating a balanced dataset. It can be easily found that the number of attack records is quite low compared to normal records. This makes sense since attacks do not usually occur as frequent as normal traffic. However, the ratio of anomalous to normal records is a major issue that can significantly affect the experiment training and learning process. To create a balanced dataset of normal/anomalous records from the CIC-IDS2017 dataset. We need to include an equal number of normal and anomalous records in both training and testing subsets. At the same time, we make sure that the same record cannot appear in both subsets, which guarantees proper training and leads to a better accuracy during testing phase. After making reference to [41], the distribution of different attack type and Benign records in training and testing subsets is summarized in Table 1.

4.3 Results and discussion

The performance of IDS is evaluated based on its capability of classifying network traffic into a correct type. The proposed method has been evaluated using the aforementioned training and testing subsets with two groups of metrics. According to the confusion matrix presented in Table 2, the first group includes specific metrics:
true positive rate (TPR), false positive rate (FPR), precision, detection rate (DR), f-measure and Matthews correlation coefficient (MCC) of each type of attack or benign traffic. The second one includes these global metrics: accuracy (Acc), precision, detection rate (DR), f-measure, attack detection rate (ADR), and false alarm rate (FAR). The mathematical calculations of the utilized evaluation metrics are explained in [42].

where the true positive (TP) is the number of actual attacks identified as attacks, true negative (TN) is the number of normal instances identified as normal, false negative (FN) is the number of attacks identified as normal instances, and false positive (FP) is the number of normal instances identified as attacks.

The experiment was performed using the CIC-IDS2017 dataset. First, essential features were identified by utilizing the proposed CFS-BA approach to evaluate the integrity of the reduced feature subset in the feature selection stage. Overall, thirteen candidate features were selected from the original 70 for the next stage. Table 3 shows the numbers and names of selected features. By implementing CFS-BA alone, the approach was seen to reduce the dimensionality drastically and eliminate the irrelevant features of the dataset. Moreover, in order to significantly improve the predictive performance of IDS, an ensemble classifier which consists of three different decision tree classifiers was used in a vote algorithm. Table 4 summarizes the classification results of the proposed IDS in the context of TPR, FPR, precision, DR, f-measure and MCC. It is observed that the TPR and FPR of most of the classifications is adequate. Although some DR values of the attacks are lower due to a fairly small number of instances, as the DR value is adequate for benign cases, the developed system can be used for intrusion detection.

4.3.1 Comparison with no feature selection. In order to evaluate the performance of the proposed model, we make a comparison between the proposed feature selection approach and without feature selection. First, as shown in Fig. 2, the comparison of the detection rate of every type of attacks or benign instances was constructed between them. According to the figure, it is observed that the performance of most of the classifications under CFS-BA feature selection is in line with the ensemble model using all original features, and some DR values of the attacks are even higher using CFS-BA, which means that the selected features are representative enough for the data and highly relevant to the prediction.

Next, the further comparison was constructed between the global performance of the proposed model and that of all the features, with accuracy, precision, DR, f-measure, ADR and FAR to distinguish attacks from benign instances. The result of the comparison on the CIC-IDS2017 dataset is shown in Table 5, Table 5(a) and Table 5(b) respectively represents the performance results based on the original features and the selected features using CFS-BA under each type of classifiers. As shown in Table 5, we observed that the performance of the proposed feature selection approach outperforms that of all features in every respect and the performance of the proposed ensemble approach achieves the highest accuracy rate of 0.968 and detection rate of 0.995 with 13 features which outperforms all other individual classifiers. In contrast, the best accuracy of the C4.5, RF, and ForestPA classifiers were 0.944, 0.953, 0.951 using CFS-BA based feature selection, respectively.

Furthermore, the proposed CFS-BA Ensemble model exhibits one of the highest scores in precision, DR, f-measure and ADR in comparison with other combined models, and slightly higher FAR than other individual classifiers within an acceptable range. The proposed CFS-BA algorithm reduced the computational cost significantly when it was applied to the ensemble model, Table 5 also shows a comparison of the consumed training and testing times based on the number of selected features. According to the
Table 4: Classification results of proposed method on CIC-IDS2017 dataset.

| Attacks                | TPR   | FPR   | Precision | DR    | F-Measure | MCC  |
|------------------------|-------|-------|-----------|-------|-----------|------|
| Benign                 | 0.995 | 0.033 | 0.968     | 0.995 | 0.981     | 0.962|
| DDoS                   | 0.996 | 0.000 | 0.999     | 0.996 | 0.998     | 0.997|
| DoS slowloris          | 0.919 | 0.003 | 0.932     | 0.919 | 0.925     | 0.922|
| DoS Slowhttptest       | 0.945 | 0.003 | 0.899     | 0.945 | 0.922     | 0.919|
| DoS Hulk               | 0.969 | 0.000 | 0.997     | 0.969 | 0.983     | 0.981|
| DoS GoldenEye          | 0.667 | 0.000 | 0.992     | 0.667 | 0.798     | 0.811|
| Heartbleed             | 1.000 | 0.000 | 1.000     | 1.000 | 1.000     | 1.000|
| PortScan               | 0.999 | 0.002 | 0.986     | 0.999 | 0.993     | 0.992|
| Bot                    | 0.482 | 0.001 | 0.850     | 0.482 | 0.616     | 0.636|
| FTP-Patator            | 0.998 | 0.000 | 1.000     | 0.998 | 0.999     | 0.999|
| SSH-Patator            | 1.000 | 0.000 | 0.998     | 1.000 | 0.999     | 0.999|
| Web Attack-Brute Force | 0.700 | 0.003 | 0.759     | 0.700 | 0.728     | 0.726|
| Web Attack-XSS         | 0.350 | 0.004 | 0.277     | 0.350 | 0.309     | 0.308|
| Web Attack-Sql Injection| 1.000 | 0.000 | 0.444     | 1.000 | 0.615     | 0.667|
| Infiltration           | 0.833 | 0.000 | 1.000     | 0.833 | 0.909     | 0.913|

Figure 2: Comparison of CFS-BA based feature selection and without feature selection in classification results.

4.3.2 Comparison with other feature selection methods. As explained in Section 4.1, the CIC-IDS2017 dataset is a recent creation and quite different from the previous ones, it reflects a more contemporary and complex threat environment. The increased number of attack classes and its highly imbalanced records(Table 1) pose a significant challenge to every machine learning approach. In order to further evaluate our proposed model, we compare it with some well known feature selection methods, namely IG(Information Gain)[43], GA(Genetic Algorithm)[44] and PSO(Particle Swarm Optimization)[45] under each type of classifiers. Likewise, in this
comparative study we use the different metrics in the context of
Acc, f-measure, ADR and FAR, Fig. 3 summarizes the global per-
formance of our model as compared to the other feature selection
methods.

First, as shown in Fig. 3(a), the accuracy of our proposed model
outperform that of IG and GA based feature selection in every
respect, and the performance of the proposed CFS-BA-ensemble
approach achieves the highest accuracy rate of 96.76%. In contrast,
the best accuracy of the IG, GA and PSO based feature selection were
94.32%, 95.64%, 95.75% with the ensemble classifier, respectively.
Similarly, Fig. 3(b) shows that our proposed model exhibits better
f-measure than IG, GA and PSO with the ensemble classifier, which
increase the value of f-measure from 0.959 to 0.981.

Next, the attack detection rate, which stands for the accuracy
rate for the attack classes, is an important indicator to evaluate
the performance of an IDS. According to Fig. 3(c), it is observed
that the attack detection rate of our proposed model ranges from
93.51% to 94.04%, which significantly exceeds other feature selection
methods under different classifiers. Moreover, as Fig. 3(d) illustrates,
the false alarm rate of our proposed CFS-BA based model ranges
from 2.38% to 3.25%, and in comparison with other feature selection
methods, our proposed model has mitigated FAR considerably and
guaranteed the effectiveness of an IDS.

5 CONCLUSIONS
In this paper, we have proposed a novel methodology which com-
nbines CFS and BA with the aim of discarding irrelevant features and
was evaluated using a novel intrusion detection dataset, namely CIC-IDS2017 and scored superior results for the TPR, FPR, precision, DR, f-measure and MCC when recognizing whether a given instance is normal or any type of attacks.

At first, we compared our proposal with a no-feature-selection model, the performance of the CFS-BA-Ensemble approach was in line with that of the no-feature-selection approach, and the computational cost of the proposed method was reduced considerably in comparison with the model using all the features. Furthermore, the performance of the proposed method was compared against recent and related approaches. Based on the experimental results, the CFS-BA-Ensemble approach acquired the highest accuracy rate (96.76%), f-measure(0.981), ADR(94.04%) and lower FAR (3.25%) in attack classes, and this issue will be considered in the future work.

Table 5: Performance results based on the original features and selected features using CFS-BA.

(a). The performance results based on the original features(70 features)

| Classifier | Acc  | Precision | DR     | F-Measure | ADR   | FAR   | Training(s) | Testing(s) |
|------------|------|-----------|--------|-----------|-------|-------|-------------|------------|
| C4.5       | 0.937| 0.962     | 0.958  | 0.960     | 0.917 | 0.037 | 5.92        | 0.53       |
| RF         | 0.949| 0.965     | 0.967  | 0.966     | 0.931 | 0.035 | 20.90       | 1.65       |
| ForestPA   | 0.948| 0.963     | 0.967  | 0.965     | 0.929 | 0.038 | 86.40       | 0.53       |
| Ensemble   | 0.953| 0.950     | 0.981  | 0.965     | 0.924 | 0.048 | 113.53      | 2.93       |

(b). The performance results based on the selected features using CFS-BA(13 features)

| Classifier | Acc  | Precision | DR     | F-Measure | ADR   | FAR   | Training(s) | Testing(s) |
|------------|------|-----------|--------|-----------|-------|-------|-------------|------------|
| C4.5       | 0.944| 0.976     | 0.953  | 0.964     | 0.935 | 0.024 | 1.06        | 0.26       |
| RF         | 0.953| 0.976     | 0.966  | 0.971     | 0.940 | 0.024 | 8.13        | 1.32       |
| ForestPA   | 0.951| 0.975     | 0.965  | 0.970     | 0.937 | 0.024 | 33.98       | 0.26       |
| Ensemble   | 0.968| 0.968     | 0.995  | 0.981     | 0.940 | 0.032 | 44.78       | 2.06       |

retaining the optimum feature subset, while the ensemble classifier based on C4.5, RF and ForestPA with the AOP algorithm is used to construct the classification model. Our methodology deals with the several challenges posed by the high dimensionality of the dataset and builds the ensemble model in order to produce better results in classification than individual classifier. The proposed scheme was evaluated using a novel intrusion detection dataset, namely CIC-IDS2017 and scored superior results for the TPR, FPR, precision, DR, f-measure and MCC when recognizing whether a given instance is normal or any type of attacks.

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