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# Hybrid Feature Selection Technique for Intrusion Detection System

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**Abstract:** The enormous volume of network traffic has created a major challenge to the Intrusion Detection System (IDS). High dimensionality's problems have made feature selection as one of the most important criteria in determining the efficiency of the IDS. The objective of this study is to seek the best-fit for selecting features that can provide a high level of detection level with low false positive rate. In this study we have selected a hybrid feature selection model that potentially combined the strengths of both the filter and the wrapper selection procedure. The potential hybrid solution is expected to effectively select the optimal set of features in detecting intrusion. The usage of several performance metrics to study the feature selection optimisation impact includes performance accuracy, true positive, true negative, detection rate, false positive, false negative and learning time. The proposed hybrid model was carried out using Correlation Feature Selection (CFS) together with three different search techniques known as best-first, greedy stepwise and genetic algorithm. The wrapper-based subset evaluation uses a Random Forest (RF) classifier to evaluate each of the features that were first selected by the filter method. The reduced feature selection on both KDD99 dataset (Network-based) and DARPA 1999 (Host-based) dataset was tested using RF algorithm classification with 10-fold cross-validation in a supervised environment. The experimental result shows that the hybrid feature selections had produced satisfactory outcome in terms of least number of features with lower processing time. It also had achieved almost 100% detection rate of known attacks on both datasets. This encouraging result has proven the usage of hybrid feature selection model in IDS environment would be a method of choice.

**Keywords:** Machine Learning; Filter-subset evaluation; Wrapper-subset evaluation; Genetic Algorithm; Random Forest

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## 1 Introduction

The rapid growth of high-speed Internet has led to an increase in data production at a staggering pace. Research by (Koff & Gustafson 2011) in 2011 predicted that data assembly will be 44 times greater in year 2020 than it was in year 2009. Currently, the ability to analyse the increased data size is still not commensurate with its growth rate. When analysing voluminous data, it is obvious that more computational efforts are needed due to its sophistication and complexity.

The need for longer processing time would significantly affect the system performance as it slows down the attack detection speed. Thus, machine-learning tools was introduced to analyse the big (high dimensional) data. The key function of the tools is feature selection. The machine would recognise the most prominent feature for continues learning. It focuses on the learning algorithm to gather the most useful information for the future prediction requirement. Meanwhile, the system would still maintain its important features of primary data with better processing time.

The Intrusion Detection System (IDS) can be described as a device or an application that detects malicious activities or policy violations within the network. IDS have been widely used in recent years as one of the main network security components. The objective of this study is to find the best-fit approach that would significantly reduced the number of features. In addition, the approach would lead to high classification accuracy with less processing time.

To achieve this objective, we had proposed a hybrid feature selection model that leverages strengths from the legacy filter and wrapper selection procedure. The proposed hybrid solution is expected to effectively select the optimal set of features in detecting intrusion. The rest of this paper is organised as follows. Section II describes the background of feature selection, while the related work is explained in Section III. The proposed method and results are presented in Sections IV and V. Section VI concludes this finding and outlines future work.

## 2 Feature Selection

Feature selection is a foundation of machine learning that has been explored for many years (Liu & Motoda 1998). It is the process of discovering the most prominent feature for the learning algorithm. The most useful data is used for analysis to achieve better future projection. Therefore, the redundant or irrelevant features need to be extracted or removed to prevent the classifier from being biased towards more frequent recording. As the effectiveness of the algorithm selected is highly dependent on the feature selection, it is imperative to minimise the selecting features errors that could reduce the detection of abnormal behaviour. Choosing the feature selection algorithm often requires expert knowledge as it is not an easy task to

determine a good set of features. Basically, there are two general methods namely filters and wrappers (Johnson & Shanmugam 2011) that currently being use in many feature-selection processes.

The two categories of filters method include filter-based feature ranking (FBFR) and filter-based subset evaluation (FBSE). FBFR ranks the applicable features by assigning weights to individual features based on the score of every single feature to the target classes; no attention is spared to interaction between features. Feature ranking is faster than filter subset as it only computes the features once. In comparison, the FBSE computes to the power of two or  $2^n$  where (n=number of features). In view that the filter ranking features are uniquely selected, it did not take into account the relationship between features. As such, it was not able to handle redundant features effectively (Tang et al. 2014). Information gain, mutual information and gain ratio are examples of FBFR.

FBSE was introduced simply to overcome the redundant features issues. It examines the whole subset in a multivariate way. It selects the relevant features and explores the degree of relationship between features. As such, selecting features in IDS, FBSE is more desirable than the FBFR (Nguyen et al. 2010). FBSE is heuristic-based and involves probabilities and statistical measures to search and evaluate the usefulness of all identified features. On the other hand, the wrapper-based subset evaluation (WBSE) uses a classifier to evaluate the worth of each feature subset. Usually, WBSE has better predictive accuracy compared to filters. This is because the selection approach is optimised when evaluating each feature subset with a particular classification algorithm. Conversely, most of the time wrappers are using classification algorithm to evaluate each set of features. This has made it excessively expensive to run. Moreover when dealing with a large database that consists of many features (Hall 1999) wrapper can become uncontrollable. Wrappers are also highly associated with the classifier's algorithm that makes it more difficult when shifting from one classifier to another. This is because the selection process needs total re-initiation.

Unlike filters, the selection criteria of features use distance measures and correlation function (Cleetus 2014). It does not require re-execution for different learning classifiers. This has made its execution much faster than the wrappers. Filters are suitable in large database environment that contains many features. Researchers have often used the filter, as an alternative to the wrapper since the later is expensive and time-consuming to run.

### 3.1 Correlation-based feature selection

In this study, we use Correlation-Based Feature Selection (CFS) that derived from Pearson correlation coefficient. The CFS is a simple filter algorithm that evaluates subsets of feature according to heuristic evaluation function. The study was based on the hypothesis "*A good feature subset is one that contains features highly correlated with the class, yet*

uncorrelated with each other” (Hall 1999). The algorithm will remove irrelevant features that have low correlations with the class. It would also screen out all redundant features as they might highly correlate with other features. The redundant feature occurs when one or more features are highly correlated with each other. The following equation from (Hall 1999) shows how the M, merit is used to select subset, S containing k number of features. Both redundant and irrelevant features are determined from  $\overline{rcf}$  where it is the  $\mu$ , mean of correlation for each feature and its class while  $\overline{rff}$  is the  $\mu$ , mean of correlation between features.

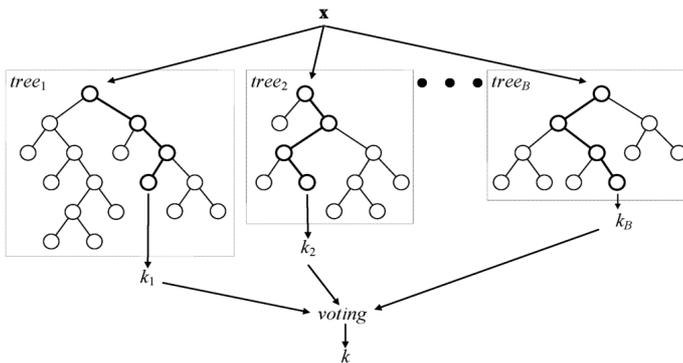
$$Ms = \frac{k\overline{rcf}}{\sqrt{k + k(k-1)\overline{rff}}} \quad (1)$$

The equation concludes that the probability of features to be selected will depend on the correlation between feature and the class as well as correlation among the features. The process would be continued explore the search space with heuristic search algorithm. The subsets with the highest merit obtained during the search would be selected.

### 3.2 Random forest classifier

The RF algorithm can be classified as an ensemble classification and regression tree (CART). This algorithm is widely used in data mining techniques for prediction, pattern recognition and probability estimation (Zhang et al. 2008), (Attal et al. 2015), and (Khoshgoftaar et al. 2007). It consists of many decision tree classifiers. Each decision tree is constructed from a different sample of the original dataset. The outputs are chosen based on a vote from each tree that indicated the tree’s decision of the class object. The most votes for the object are from the best individual trees.

**Figure 1** A general architecture of a random forest



As the RF generates many classification trees, each tree is constructed by a different bootstrap sample from the original data using a tree classification algorithm. Each tree gives a vote that indicates the tree’s decision about the class of the object. The forest chooses the class with the most votes for the object. Out-of-bag (OOB) error is used as validation during the tree growth. It is described as the average of the classification error that is connected to each tree  $T_b$  using the  $OOB_b$  sample. After the forest is formed, a new sample  $x_i$  needs to be classified as per the following equation:

$$\hat{C}_{rf}^B(x_i) = \text{majority vote} \{ \hat{C}_b(x_i) \}_1^B \quad (2)$$

where  $\hat{C}_b(x_i)$  is the class that assigned by the tree  $T_b$ .

RF as a classification technique has been extensively used due to its robustness in handling high dimensional data (T. Hastie, R. Tibshirani 2009) with small number of available learning samples (Htun & Khaing 2013). It also runs on nominal data and resolves over-fitting drawback issues effectively.

### 3.3 Heuristic Search

The search algorithm performance is important in selecting the best-fit features. One of the popular search techniques used is called the greedy algorithm. The features are added or removed from the subset until the algorithm has considered all possible selections. When the algorithm is added to the feature subset, it is recognised as “forward selection”. On the other hand, when the feature subset is deleted, it is called as “backward elimination” (Guyon 2003). This approach was not a popular choice as could suffering from the “nesting effect”. Furthermore, when features are removed from top-down, the algorithm is unable to place them back onto the selected subset. As such, the final subset may not possess the best features. The final subset would only be considered when it has shown better performance over than the previous subset (Wald et al. 2013a). This approach indicates strong assumption that the features are completely independent when using evaluation metric on an individual feature (Diao & Shen 2012).

The best-first search algorithm is an artificial intelligence approach that allows a backtracking search. Similar to greedy algorithm, the best-first search technique is also used to explore the most promising path by moving through the search space and making changes to the current feature subset. The most recent subset is checked at each step. If it is found to be better than the previous subset, then the recent will replace the previous subset (Wald et al. 2013a). Unlike the greedy algorithm, the best-first algorithm can go back to the previous subset and continue from there if the search begins to look less promising. The best-first entire space exploration characteristic has made it common to stopping criterion. It normally limits the number of expended subsets that return without any improvement.

Genetic algorithm (GA) is an adaptive search technique that uses biological evolution as natural selection principle in solving a problem (Hassan 2013). It is based on the evolution theory proposed by Darwin. According to Darwin, the survival of the fittest is the concept to converge optimal solution and make effective population. The algorithm applies iterative process that evolves when applying selection, crossover and mutation operators to the members of the current generation (Bagyamani et al. 2013). The selection process will identify the fittest subset of the current population to serve as a parent for the next generation. Crossover operators are a primary exploration mechanism for GA, combining different features from a pair of subsets to form a new subset. The operation will takes 2 feature subsets (parents) and reconstruct the 2 new subsets (child’s). The mutation operator’s main function is to restore the diversity that may be lost during the repeated

selection and crossover application. It modifies certain value in a subset randomly. During the evolution search, the fittest of the subset is estimated using the fitness function. Using the earlier three operators processes, a better fitness feature subsets would have greater chance of being selected and forming a new subset. The genetic search gives a global optimum solution and is more robust compared to the greedy approach and best-first. However, it does come with some computational effort (Vafaie & Imam 1994).

### 3 Related Work

Feature selection process has attracted interest of many researchers due to its potentiality in reducing high dimensional data. Feature ranking algorithm was introduced merely to select the top six features based on rank (Sung & Mukkamala 2004). The author uses three ranking algorithms of Support Vector Machines (SVM), Multivariate Adaptive Regression Splines (MARS), and Linear Genetic Programming (LGP). The algorithm would select the best feature and make performance comparison between each algorithm. The detection would be programmed to detect Probe and Dos attack. The LGP could achieve higher accuracy rate in detecting both types of attacks compare to other algorithms. This approach is however effective to specific type of attacks only. It is not fit for others such as R2L and U2R attacks.

The speedy computation ability of the filter ranking has made it suitable for very large datasets. For instance (Wald et al. 2013) use filter ranking to reduce 480 to 40 features. The author is comparing three different approaches of feature selection (filter-rank, filter-subset evaluation and wrapper-subset evaluation) to find the best method to select the relevant features. Three different feature selections with six different classifiers, 5-Nearest Neighbors (5-NN), Logistic Regression (LR), Multi-Layer Perceptron (MLP), Naive Bayes (NB), Random Forest with 100 trees (RF100), and Support Vector Machines (SVM) were used to achieve the best results. As recommended by the author, the filter ranking process executed in high dimension data performs better when using SVM classifier techniques compare to the other two. Nevertheless, the author had also proved that the filter ranking method is more competent compared to the filter subset and the wrapper subset. However there was no explanation on the methods implemented in choosing the top 40 features from the ranking table. This uncertainty might affect the final optimal set of features since it may contain irrelevant features.

Another filter ranking was implemented by (Ambusaidi et al. 2014) in his research where he proposed hybrid feature selection by combining both Mutual Information (filter ranking) and wrapper that using Least Square-SVM as classification algorithm in removing irrelevant and redundant features. Mutual Information provides a good measurement to find relevant feature by quantify the amount of information to the output class. The proposed criterion function  $G$  has given compliments to mutual information in removing redundant features. Although the results shows significant reduced of features, the false positive and the detection rate still can be improved.

In relation to the calculation of features selection

relevancy, (El-Khatib 2010) has proposed Information Gain Ratio (IGR) to replace the Information Gain (IG) calculation method. This is because the IG is normally biased towards features that have high distinct value. The selected features are ranked based on score derived from the IGR calculation. The K-Means classifier is then used to determine the best-fit feature-set based on performance results accuracy. The selection process would end when the current subset performance drops below the previous subset accuracy. The selected features are tested with 3 types of artificial neural network (ANN) architecture namely Perceptron, Multilayer Backpropagation Perceptron (MBP) and Hybrid Multilayer Perceptron (HMP). Although HMP has lower false positive rate and took longest time in learning model, its classifier has outperformed both the Perceptron and the MBP. Nevertheless, there were no significant detection rate differences between the proposed HMP and MBP.

It proved less accurate when classifier was used singly to evaluate performance accuracy compared to using ensemble technique (combining more than one classifier) (Mukkamala et al. 2004). (Zainal et al. 2008) proposed neural fuzzy inference system (ANFIS) and Linear Genetic Programming (LGP) algorithms in detecting four main types of attacks of Probe, Dos, R2L and U2R. This ensemble technique was implemented with a reduced set of features (between six to eight only) for each type of attacks. This technique has achieved more than 99% detection rate for R2L and U2R attack types and an average of 99.15% accuracy for all attack types.

In selecting the best-fit classifier (Zaman & Karray 2009), the author has compared his approach with two different classifiers namely Neural Network (NN) and Support Vector Machine (SVM). The author has proposed a novel method called Enhanced Support Vector Decision Function (ESVDF) to select features based on rank and use backward elimination ranking (BER) and forward selection ranking (FSR) to calculate the correlation between features. The comparison of both algorithms reveals that the NN had better performance than the SVM, with 99.55% accuracy. The method had improved in reducing the number of features and the time taken to build a model, by a negligible margin of 0.08% and 0.11% for NN and SVM, respectively. Nevertheless, the accuracy rate is still lower than when using full features.

Numeral feature selection approaches had been introduced in the past. Nevertheless, achieving low false detection and high attack recognition capabilities are still a major challenge. There are three main different of our approaches compared to existing hybrid selection (Ambusaidi et al. 2014) and (Singh & Tiwari 2015). The first approach uses correlation-based selection to determine the worthiness of each feature by removes redundant features that exist inside filter rank. The second approach analyses and determine the best-fit search strategy. Here, the top three search algorithms of 'best-first', 'greedy' and 'genetic search' are concisely evaluated. The third approach uses RF as a classification algorithm in the evaluation process. This is due to its effectiveness for high dimensional data execution, complemented with capability of solving over-fitting issues (T. Hastie, R. Tibshirani 2009). The concept of our proposed hybrid feature selection technique

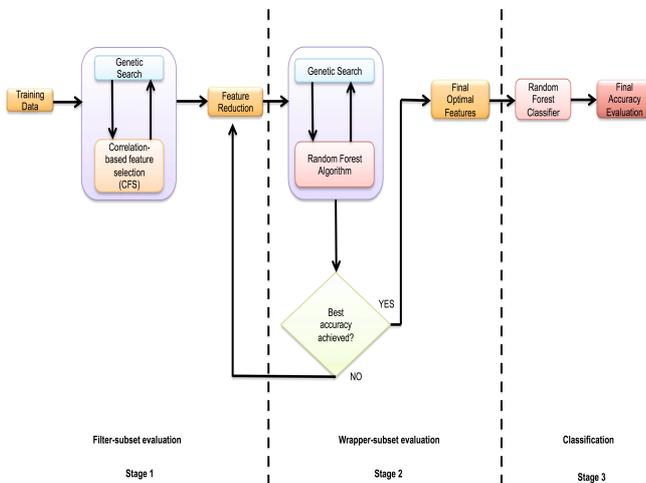
was based on leveraging the strengths of both the filter and the wrapper techniques.

#### 4 The proposed Hybrid Feature Selection Technique

Figure 2 shows the process flows for building hybrid feature selection. The process is divided into 3 stages as follows:

In Stage 1, the process starts with the filter-subset evaluation. It processes the original features  $M$  to generate new set  $L$  of reduced features, where  $L \subseteq M$ . We proposed the CFS approach due to its robustness in removing redundant and irrelevant features. In this research, CFS is used to prevail over problems in feature ranking (Information Gain, Gain ratio) where redundant features exist (Wald et al. 2013) and reduced features are usually defined without performing further examination. We are not considering exhaustive search because it is proven as not suitable to use in large dataset (Guyon 2003) due to its high complexity. As such, we had applied heuristic search techniques and chose a genetic algorithm as the search function. This technique had demonstrated better performance during our experiments between the best-first and the greedy search methods, refer to table 3 & 4. Furthermore, in this stage it is crucial to help truncate the computational effort for wrapper approach, which only deals with reduce feature set compared to the original set of features.

**Figure 2** A proposed hybrid feature selection design



In Stage 2, the reduced feature set  $L$  gathered from the FBSE had been continued with WBSE to produce the final optimum features  $K$ , where  $K \subseteq L \subseteq M$ . The hybridisation of both the filter and wrapper was proposed due to the filter approach alone would not be able to find the best available subset as it is less dependent on the classifier (Peng et al. 2010). On the other hand, the wrapper approach is believed to be more effective and to produce better accuracy. However it is computationally expensive when dealing with large dataset. In view of the above limitations, we had leveraged the strength of both methods to form a better-synergized approach. In WBSE, we use the RF classifier to evaluate the selected features using the genetic search and produced the final  $K$  feature subset. The search will

continue to train new model for each subset and will stop when the final optimum subset has been found.

Stage 3 is called the classification stage. In this stage, the final optimum subset  $K$ , produced by WBSE, was tested by the RF classifier with 10-fold cross validation. Eight performance metrics were used in this experiment and the output indicates that the hybrid feature selection approach yielded better results compared with other approaches.

#### 5 Experiments and Results

##### 5.1 Experimental Setup

These experiments have been obtained using WEKA data mining tool (Anon n.d.) version 3.7.1 on Pentium core i7 in Windows environment.

##### 5.2 Network and host based dataset

We applied KDD99 dataset (network-based) and DARPA 1999 dataset (host-based) to test the proposed methods in two different environments. Initially we were quite sceptical on the DARPA dataset (McHugh 2000) performance especially on its maturity over 15 years. Later we found out that it was actually the most comprehensive and extensively used dataset. In fact, the DARPA dataset has been recognised as the standard benchmark by many researchers in this field (Xiang & Zhou 2006) and (Yassin et al. 2014).

The KDD99 intrusion detection dataset is based on the Defense Advanced Research Projects Agency (DARPA) 1998 initiative that has created a benchmark in evaluating different methodologies. DARPA 1999 was the improved version of DARPA 1998, as it contains more new attacks than the previous dataset. In DARPA 1999 dataset, we had selected a host with the IP address 172.016.112.050 because it had the most number of attacks among hosts within the dataset (Shamsuddin & Woodward 2007).

Table below shows the description of both dataset used in this experiment.

**Table 1** KDD99 Training Dataset

<i>Class name</i>	<i>Instance</i>	<i>Percentage %</i>
Normal	97271	19.6
Attack (DoS, Probe, U2R and R2L)	396743	80.4

**Table 2** DARPA 1999 (host-based) 172.016.112.050

<i>Class name</i>	<i>Instance</i>	<i>Percentage %</i>
Normal	465409	87.6
Attack (DoS, Probe,	65821	12.4

KDD99 Training dataset consists of 494014. Out of which only 19.6% or 97,271 of the data were recognised as normal data. The attack was divided into four categories namely, Probe (4107), DoS (391458), U2R (59) and R2L (1119) (Jalil et al. 2010). In DARPA 1999 dataset, 87.6% or 465,409 were representing normal data while the remaining 12.4% or 65,821 were attack data.

### 5.3 Results and analysis

During the experiment, we observed that both filter and hybrid methods had selected the same attributes ( $f_6, f_{23}, f_{31}, f_{37}$ ) in KDD99 and ( $f_{28}, f_{31}, f_{32}$ ) in DARPA1999. We found that this is due to the obvious attack pattern demonstrating by those features. For instance, feature 23 (count: number of connections going into the same host in the past two seconds) has indicated a significant pattern of Probe and DoS attacks. The nature of these attacks was targeting a specific host by sending huge traffic volume to the same host to flood the whole network and used-up all available resources. Unlike the U2R and R2L pattern, the attack behaviour usually takes longer time to access the system to guess the password or by brute force attack. This will make feature 1 (duration: number of seconds of the connection) more important in detecting these types of attacks. In this research process, we found that the greedy and best-first approaches select the same features. This was due to their nature of sharing similar space search techniques. On the other hand, genetic algorithm those pick-up different features should provide global optimum solution.

Table 3 & 4 shows comparison of performance metrics among the three different search methods (best-first, greedy-stepwise and genetic search) on filter-based subset evaluation and hybrid approach using KDD99 and DARPA 1999 datasets. Out of the three-search methods, genetic search has scored the highest accuracy rate of 0.42% more than the other two search methods. We then hybridise the reduced features from filter with wrapper RF classifier. Although filter method could also show some performance improvement, but when combined with wrapper approach, it had recorded significant features reduction from 21 to 12 and improved the time building model by 14%. Moving on, we had tested the hybrid method on DARPA 1999 host-based environment. The result shown was significant reduction of features from 33 to 5 with higher accuracy and detection rate by 1.22 % and 0.8%. The results clearly

demonstrated the accuracy detection is either the same or better with considerable reduction of features set. Thus, it is an essential step to utilise feature selection techniques in building IDS.

### 5.4 Performance metrics

In this study, we have considered several performance metrics (Number of Features, Time, True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN), Detection Rate and Accuracy) as a benchmark to evaluate the proposed method (Wald et al. 2013b).

- a) Number of Features: Feature used during experiment.
- b) Time: The time measured in seconds taken by classifier to build the model on dataset
- c) True Positive (TP): To estimate the amount of attack data detected is actually attack data
- d) True Negative (TN): To estimate the amount of normal data detected is actually normal data
- e) False Positive (FP): To quantify the amount of normal data detected as attack data
- f) False Negative (FN): To quantify the amount of attack data detected as normal data
- g) Detection Rate: Is the proportion of detected attacks among all attack data
- h) Accuracy: It is measure in percentage, where instances are correctly predicted

$$Detection\ Rate\ (DR) = \frac{(TP)}{(TP) + (FN)} \quad (3)$$

$$Accuracy\ (ACC) = \frac{(TP) + (TN)}{(TP) + (TN) + (FP) + (FN)} \quad (4)$$

**Table 3** Performance metrics of different feature selection approaches for KDD99 (Network-Based) dataset

<i>KDD99 DATASET (Network-Based)</i>								
	<i>Number of Features</i>	<i>Time</i>	<i>True Positive</i>	<i>True Negative</i>	<i>False Positive</i>	<i>False Negative</i>	<i>Detection Rate</i>	<i>Accuracy</i>
Full Feature	41	122.71s	99.98%	99.97%	0.03%	0.01%	99.99%	99.98%
Filter (Best First)	6	11.94s	99.57%	99.53%	0.47%	0.43%	99.57%	99.56%
Filter (Greedy Stepwise)	6	11.94s	99.57%	99.53%	0.47%	0.43%	99.57%	99.56%
Filter (Genetic Search)	21	16.27s	99.99%	99.97%	0.03%	0.01%	99.99%	99.98%
<b>Proposed Method (Filter + Wrapper)</b>	<b>12</b>	<b>13.98s</b>	<b>99.99%</b>	<b>99.97%</b>	<b>0.03%</b>	<b>0.01%</b>	<b>99.99%</b>	<b>99.98%</b>

**Table 4** Performance metrics of different feature selection approaches for DARPA 1999 (Host-Based) dataset

<i>DARPA 1999 (Host-Based)</i>								
	<i>Number of Features</i>	<i>Time</i>	<i>True Positive</i>	<i>True Negative</i>	<i>False Positive</i>	<i>False Negative</i>	<i>Detection Rate</i>	<i>Accuracy</i>
Full Feature	33	24.24s	98.71%	99.81%	0.19%	1.29%	98.71%	99.68%
Filter (Best First)	6	21.61s	98.71%	99.95%	0.05%	2.16%	97.85%	99.69%
Filter (Greedy Stepwise)	6	21.61s	98.71%	99.95%	0.05%	2.16%	97.85%	99.69%
Filter (Genetic Search)	8	22.43s	99.24%	99.94%	0.06%	0.76%	99.24%	99.85%
<b>Proposed Method (Filter + Wrapper)</b>	<b>5</b>	<b>17.12s</b>	<b>99.51%</b>	<b>99.99%</b>	<b>0.01%</b>	<b>0.49%</b>	<b>99.51%</b>	<b>99.93%</b>

### 5.5 Respective Study

Table 5 shows comparison between our hybrid feature selection with other feature selection methods that use similar KDD99 dataset, we noted that it produced better accuracy rate. Thus, our hybrid feature selection method has proven a better option in detecting network and host traffic intrusion.

**Table 5** Comparison results between our approach and others feature selection approach on KDD99 dataset

<i>Methods</i>	<i>Features</i>	<i>False Positive</i>	<i>Detection Rate</i>	<i>Accuracy</i>
Enhanced Support Vector Decision Function (Zaman & Karray 2009)	9	0.03%	-	99.58%
Generic Feature Selection (Nguyen et al. 2010)	18	-	-	99.60%
Hybrid Classification Algorithm (Singh & Tiwari 2015)	20	-	-	99.70%
Least Square SVM (Ambusaidi et al. 2014)	6	0.07%	99.93%	99.90%
<b>Proposed Method</b>	<b>12</b>	<b>0.03%</b>	<b>99.99%</b>	<b>99.98%</b>

## 6 Conclusion and future works

The objective of the research was to capitalise on the strengths of both the filter and the wrapper approaches as the pre-processing phase in detecting intrusion. We experimented the hybrid feature-selection model by combining the strengths of the two FBSE and WBSE approaches. Initially, the FBSE was to concentrate on reducing the WBSE computational effort by filtering the insignificant and redundant features. Then it continues searching for the optimal subset that was first picked up by the FBSE to improve the classification performance. The final features subset generated from the hybrid process was tested using RF classifier and 10-fold cross validation. The FBSE was also used to resolve the filter ranking issue of existing redundant features. The proposed hybrid feature selection was evaluated with two types of datasets (network-based and host-based) mainly to allow different integration testing environment. Individually, FBSE approach is capable enough to demonstrate some performance improvement. However, the newly generated hybrid combination model of FBSE and WBSE approaches had yielded better performance improvements in terms of detection time, accuracy, and detection rate. It also recorded

having low false alarm rate. Moving forward, we will proceed with the research on the ability of this newly discovered hybrid model in detecting novel attacks.

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