International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-11 Issue-4, November 2022

Hybrid Sequential Feature Selection With Ensemble Boosting Class-based Classification Method

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***Abstract:** The rapid rise in hacking and computer network assaults throughout the world has highlighted the need for more effective intrusion detection and prevention solutions. The intrusion detection system (IDS) is critical in identifying abnormalities and assaults on the network, which have grown in size and scope. IDS prevents intruders from gaining access to information in the field of network security as a result. The use of IDS is critical for detecting various types of attacks. Because the network traffic dataset contains a large number of features, the process of selecting and removing irrelevant features improves the accuracy of the classification algorithms. For the fact that a large dimension allows us to include more data, the feature vector can be built by combining different types of features. Contains a lot of redundant or irrelevant data can cause confusion. Over-fitting issues and a decrease in the generalization capacity of the model. Solving such a problem necessitates a sequence of feature selection methods the boosted maximum relevance maximum distance (BMRMD) method can report on the contribution of each feature as well as the predictive accuracy based on the best feature set. As a result, the best features in this study were chosen using the BMRMD assesses feature redundancy to determine feature relevance to the target class based on optimum ensemble feature classification.*

***Keywords:** Classification, Ensemble, Feature Selection, Intrusion Detection, Machine Learning, Network Security.*

I. INTRODUCTION

Intruders have proliferated significantly as the world's internet technology service has developed. As a result, Intrusion Detection Systems (IDS) in the field of network security stop intruders from accessing data. IDS is critical for identifying various assaults. Normally, the network traffic dataset comprises so many features, the feature selection, and removal step improve the classification algorithms' accuracy needed to select the influence features at first. Feature selection is a process aimed at filtering out unrepresentative features from a given Dataset, usually allowing the later data mining and analysis steps to produce better results. However, different feature selection algorithms use different criteria to select representative features, making it difficult to find the best algorithm for different domain datasets. The limitations of single feature selection methods can be overcome by the application of ensemble methods, combining multiple feature selection results. As a result, the BMRMD was utilized to choose the best features in the current study in present work. BMRMD aims to identify features' relevance to the target class by measuring feature redundancy. When an unbalanced dataset is handled by typical machine learning techniques results in a bias-to-majority problem. Employing such algorithms directly claiming the class with infrequent events is frequently misclassified since they presume that the sizes of both the majority (also known as a "negative") and minority (also known as a "positive") classes are roughly equal. When this problem arises on an unbalanced dataset, the accuracy of classifying the more relevant minority class can be disappointingly poor despite a high overall classification accuracy. Another essential aspect of an unbalanced dataset that requires our attention is the imbalanced ratio, which is derived by dividing the number of observations in the majority class by the number of observations in the minority class. The bias-to-majority problem worsens as the uneven ratio grows. Class imbalance occurs when the number of observations in one class exceeds the number of observations in another class, despite the fact that the former class is less relevant than the latter.

1.1. Motivation

The ensemble classification approach incorporated structural and evolutionary information from features to create an incursion predictor to prevent the problem. To improve the prediction performance of structure-based predictors, Zhao etal presented a new volume correction fraction based on the energy function. However, many feature sequences lack structural information, which makes the use of structure-based predictors in the post-genomic age difficult [1,19]. In comparison, these sequence-based and structural-information-independent predictors are more favorable for prediction. To address a ass imbalance problem, two conventional approaches have been utilized [2]: At the data level, change the majority or minority class distribution to allow the classification algorithm to handle an imbalanced dataset evenly this type of alteration is known as resampling and can be accomplished by raising the number of minority data samples or decreasing the number of majority data samples.

Manuscript received on 18 September 2022 | Revised Manuscript received on 25 September 2022 | Manuscript Accepted on 15 November 2022 | Manuscript published on 30 November 2022.

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To describe them oversampling and under sampling are made simple by randomly removing some data from the majority class and randomly replicating minority class patterns, respectively. Alternative to randomly resampling an imbalanced dataset, there are numerous other approaches for balancing it. For example, Ramentol et al. [3] present a strategy that combines oversampling and undersampling approaches to produce a balanced dataset that achieves the limit of information loss and addition. The algorithm-level solution tweaks existing classification algorithms to improve a classifier's accuracy when dealing with minorities. At the algorithm level, the most popular method is a cost-sensitive method, which attaches distinct misclassification costs for each class during the learning process. [4] proposes a cost-sensitive decision tree approach ensemble that is effective. When dealing with an imbalanced dataset, it achieves better results than the latter without increasing the processing time. The remainder of this work is arranged in the following manner. The associated work is described in Section 2. Section 3 presents the HSFEBM algorithm, a new Hybrid Sequential Feature Selection with Ensemble Boosting class-based classification method. We undertake an empirical study to evaluate HSFEBM in Section 4. Finally, in Section 5, we summarise and draw some implications from the current research

II. RELATED WORK

Identifying discriminative characteristics and decreasing computing time is critical in data pre-processing of imbalanced datasets [5]. When machine learning algorithms are used to deal with an unbalanced dataset, they frequently run into a bias-to-majority issue. However, if a subset of characteristics more closely related to minority class information is used as training data, classification results may be skewed toward the minority class, which is undesirable in practice [6]. Filter, wrapper, and embedding techniques are the three types of feature selection methods. They choose a subset of traits in a different way, as illustrated in Fig. 1. Feature selection is widely used to contribute to a more compact model [7], as well as reduce the dimensionality of the input. To figure out the relationship between data points and labels and study how they are related.

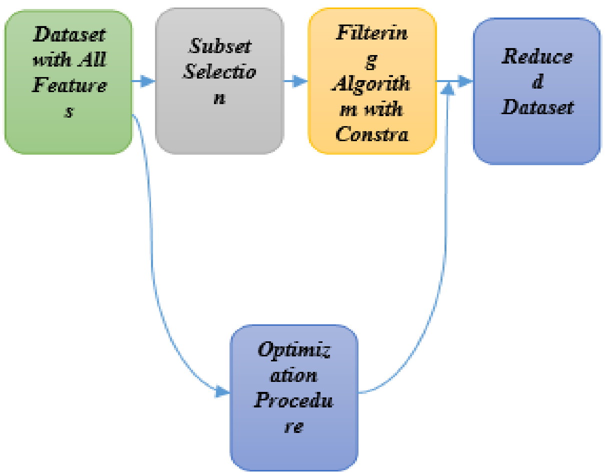

Fig-1. Process of Ensemble Feature Selection methods

Entropy is a measure of a dataset's homogeneity and probability distribution. It tells us how much more information we'd obtain if we knew how valuable the feature is [8]. The presence of high feature dimensionality is one of the primary challenges in using IDS for attack detection [9]. The goal of feature selection is to locate useful attributes among the original attributes in order to reduce the number of dimensions. In order to give acceptable prediction results, the dataset must be reduced and categorized into a set of features that reduces the influence of irrelevant and noise variables. Regardless of the algorithm employed by the IDS to detect attacks, there is still the issue of a high false-positive rate, which translates to a huge number of alarms being triggered that have nothing to do with a real threat or attack [10]. A large number of false positives adds to security analysts' burden by making it difficult to prioritize the true warnings issued by an IDS. Traffic overload, IDS misconfigurations, and inconsistencies in detection algorithms are among other issues that might result in false positives. Luo and Chen's principle of correlation underpins the sequential group selection approach for additive models. It sequentially picks features based on the strength of the features' correlations with the response's residual [11]. The multiple correlation coefficient is used to assess the correlation between a composite feature and the residual, while Pearson's correlation coefficient is used to assess the correlation between a single feature and the residual. Maldonado et al. [12] propose an SVM-based wrapper approach. Because of its inherent ability to partition a dataset, their method can avoid an over-fitting problem. They also discovered that their strategy, which employs a Kernel function, yields superior outcomes than others that do not. One disadvantage of their suggested technique is that it employs backward elimination, which is computationally expensive when dealing with multi-dimensional datasets. Moayedikia et al. [13] present a new feature selection approach based on symmetrical uncertainty and harmony search. It works well in the situation of a group of features with the same weights applied to them. Wrapper techniques are similar to embedded methods. Classification algorithms and feature selection are connected. Embedded methods have a stronger relationship than wrapper methods. Embedded methods are a form of filter/wrapper method combo. It employs classification algorithms with a built-in feature selection capability. The information that can be used to distinguish between benign and malicious applications is captured in part by the methods discussed above. A detector builder may face the following difficulties while picking features [14].

- The process of extracting characteristics is rarely automated and is dependent primarily on human expertise.
- The derived features do not fully cover the major distinguishing aspects of samples.

Retrieval Number: 100.1/ijrte.D72981111422
DOI: 10.35940/ijrte.D7298.1111422
Journal Website: www.ijrte.org

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- To use a large number of indicators improves detection accuracy
- Adds redundancy and slows down training performance. Because of the vast number of possible combinations, a complete manual search is impossible.

Algorithmic classification is the majority method that is computationally intensive [15]. Forward selection, backward elimination, and recursive feature removal are some of the most commonly used approaches for feature selection.

Focuses on the use of machine learning methods in IDSs for feature selection and ensemble-based detection [16]. Features are categorized based on the above-mentioned concerns, as well as their goals and characteristics.

2.1 Limitations of related works

Some limitations and flaws of the works [17] are revealed after examining the data acquired from the literature connected to feature selection:

- For diverse datasets, the best detection algorithms or tactics have yet to be determined.
- A correct feature subset is lacking in order to train quicker with less computing and achieve optimal performance in detecting intrusion with high accuracy and fewer false alarms.

As a result, there's a lot of solution space and extra features [18, 20]. Furthermore, in a wide solution space, a significant number of uncorrelated features yield local optima with the proposed method.

III. PROPOSED METHODOLOGY

The ensemble method is a concept that combines the findings of a group of learners into one. An ensemble can incorporate many learners to obtain more precise and trustworthy predictions. To generate and incorporate learners, a variety of approaches might be used. The most difficult part of ensemble learning is deciding the algorithms to use to build the ensemble and which decision or fusion functions to use to combine the outcomes of these algorithms. The system with an ensemble of components First, the empirical reason is based on a lack of sufficient knowledge to categorize the best hypothesis in the query space accurately. Second, the computational description is intended to address the problem that most machine learning approaches may become stuck in local optima when searching for the ideal answer. Finally, the justification for representation is to address the issue of numerous machine learning approaches failing to appropriately describe the border of the sought-after choice. Creating and merging an ensemble consists of two major steps. A set of base classifiers must be assembled during the creation process. During the combining phase, the choice is made on how to combine the findings of the basis classifiers. The ensemble concept was used to build many well-known current machine learning methods. Bagging, boosting, and stacking are three often used ensemble models. Bagging (variance), boosting (bias), and stacking (predictions) are minimized using such strategies, which combine several learning models into a single model. The general design methods of the ensemble are demonstrated in Fig.2.

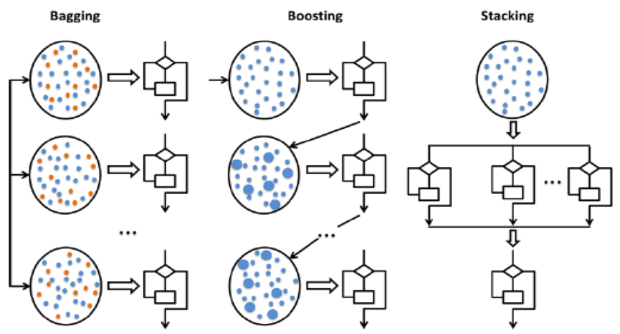

Figure.2. General Ensemble Designs

In this work, Ensemble Boosting-based classification method has been used for intrusion detection. A weak learner that produces classifiers that can modestly outperform random guessing can be transformed into a powerful learner that can correctly categorize all but a small fraction of cases. By resampling the data and merging the results by majority vote, the boosting developed a group of classifiers. In boosting, re-sampling is used to deliver the most detailed training data to subsequent classifiers. In ensemble boosting produces three classifiers connected. the first is constructed using a randomized subset of the available training data. The knowing data component of the data provided to the first classifier is used to train the second classifier. Because the first classifier correctly identified half of the occurrences in the training dataset and misidentified the other half, the second classifier was used. Finally, occurrences, where there was a dispute between the first and second classifiers, are used to gain information for the third classifier. A majority vote would be used to merge the three classifiers' outputs. The usage of distinct subsets of characteristics for each model is a good way to approach ensemble generation. Ensemble feature selection is the process of finding a collection of feature subsets for assembling an ensemble. Traditional feature selection techniques seek to discover the optimal feature subset that is appropriate for both the learning issue and the learning algorithm; however, ensemble feature selection seeks to find a set of feature subsets that increase diversity among the base classifiers.

2.2 Proposed Hybrid Sequential Feature Selection Ensemble Boosting Class-based Classification Algorithm

The process of developing proposed HSFEBM classifiers and picking a subset of the generation is repeated. The population comprises the ensemble, is made up of the fittest individuals after a predetermined number of generations. Each individual is represented by a constant length string of bits, with each bit corresponding to a distinct attribute. Uniform crossover is used by the crossover operator, in which each feature of the two children receives a value from one of the parents at random. The mutation operator changes a number of bits in an individual at random. Integration is the process of deciding which classifiers to use or how to integrate the findings generated by the underlying classifiers. A number of ways to selection and combination have been offered.

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Straightforward voting (also known as majority voting) is one of the most common and simple strategies for combining the results of the basic classifiers. In the voting, each base classifier's output is regarded as a vote for that particular class value. The final categorization is determined by the class value that receives the most votes. Weighted Voting (WV), in which each vote has a weight proportionate to the estimated generalization performance of the corresponding classifier, performs better than simple voting in most cases. In the proposed ensemble approach the three classification models as Support Vector Machine, Artificial Neural networks, and Random Forest are used with genetic sequential feature selection in our methodology. The model learns the dataset and categorizes each piece of information individually. The final categorization is determined as follows in the ensemble approach:

- Based on their correctness, each classification from the base algorithms is assigned a weight of 0 to 1.
- When the classifiers agree on classification, the decision is made based on that classification.
- If the classifiers disagree, the classifier with the highest weight is considered.

For the sample reweighting strategy initially given a weight of 1/n, the number of training samples is denoted by n. The sample weights are then calculated as a function of the preceding iteration's classification error in each subsequent iteration up-weights all misclassified data equally according to (1).

$$\alpha = \log \frac{1-err}{err}$$

$$\omega_{j+1} = \omega_j . \exp(\alpha); \forall \ \mathrm{j} = 1, 2, \ldots \mathrm{n} \quad (1)$$

Where *err* is the classification error from the previous iteration, ω_j be the sample weight for a sample *at* the j*th* iteration. This method combines the viewpoints by selecting the class predicted by the majority of the ensemble perspectives. In this scenario, there are three points of view, each of which can vote for normal (+1) or anomalous (+1). (-1). If the final vote is positive, the final perdition will be normal; otherwise, an anomaly will occur as shown by (2).

$$h(x) = \sum_{k=0}^{2} p_{k+1}(x_k) \quad (2)$$

2.3 Proposed HSFEBM Algorithm

Input: Dataset D with p features, n samples, and the output y at n classes

Output: X^i be the subset of selected features for class-based classification at the ith iteration

Initialize: i=0; X_0=ϕ; Sample weight $w_0 = 1/n$

Choose: Stopping condition $\{\varepsilon, p'\}$ and parameters m, p, y and classifiers H_1 and H_2

While i<=p' do

fit H_1 to D with ω^i and rank all the features

fit H_2 to $\{\chi^{i-1}, x^i\}$ for all x in the top m ranked features

find the best performance features x^i in cross-validation

for i=1 to n do

p=Σ (SVM (Train x) +ANN (Train x) +RF (Train x) * GBOO(x)

End

Compute $\Delta c = c[H_2(x^i)] - c[H_2(x^{i-1})]$

if $\Delta c > \varepsilon$ and $x^i \notin X$ then

set $x^i = \{\chi^{i-1}, x^i\}$

fit H_1 to X^i to find the class probability P_c and compute α^i

$$\alpha^i = -\sum_{1}^{n} y \log(p_c)$$

Update $w_j^{i+1} = w_j^i . \alpha^i; \forall j = 1, 2, \ldots. n$

Re-normalize $w_j = \dfrac{w_j^{i+1}}{\sum_{j=1}^{n} w_j^{i+1}}, \forall j = 1, 2, \ldots. n$

reset =0;

i+=1;

else

re-initialise $w_j^i = \dfrac{1}{n} \forall j = 1, 2, \ldots. n$

reset +=1;

end

end

IV. EXPERIMENTS AND DISCUSSIONS

To deliberately select significant features for KDD Cup Dataset, Sequential Feature Selection was utilised. For all classes, the original 41 traits were reduced to 15, which differed by class. After that, the reductions were fine-tuned using ensemble boosting class-based categorization has more information on the feature selection process. Table 1 summarises the obtained class-specific characteristics. The number of reduced features varies between 6 and 8, indicating a reduction of nearly 80%.

Table.1 Class-Specific Feature Set

Class	Feature set
Normal	f12, f31, f32, f33, f35, f36, f37 and f41
Probe	f2, f3, f23, f34, f36 and f40
DoS	f5, f10, f24, f29, f33, f34, f38 and f40
U2R	f3, f4, f6, f14, f17 and f22
R2L	f3, f4, f10, f23, f33 and f36

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The classifiers are compared in Tables 2 and 3 in terms of classification accuracy, precision, recall, TPR, FPR and F-measure. In the two phases, Table 4 shows the accuracy of each classifier in classifying different classes in the KDD Cup dataset.

Table. 2 Phase I examination result

Classifier	*Accuracy*	*TPR*	*FPR*	*Pre*	*Recall*	*F-Msu*
MLP	92.90%	0.944	0.085	0.932	0.939	0.931
KNN	92.13%	0.937	0.093	0.925	0.932	0.926
J48	94.29%	0.951	0.054	0.949	0.945	0.944
HSFEBM	95.12%	0.952	0.048	0.958	0.955	0.951

Table. 3 Phase II examination result

Classifier	*Accuracy*	*TPR*	*FPR*	*Pre*	*Recall*	*F-Msu*
MLP	95.60%	0.956	0.077	0.96	0.969	0.962
KNN	94.83%	0.949	0.086	0.955	0.962	0.956
J48	96.93%	0.960	0.050	0.971	0.973	0.971
HSFEBM	96.99%	0.962	0.038	0.974	0.975	0.972

Table. 4 Classification Accuracy for different classes

Classifier	**Class**	**Phase I**	**Phase II**
MLP	***Normal***	86.00%	86.90%
	Probe	87.90%	88.80%
	DoS	80.00%	80.90%
	U2R	83.80%	84.70%
	R2L	78.96%	79.86%
KNN	***Normal***	92.50%	93.40%
	Probe	92.80%	93.70%
	DoS	84.80%	85.70%
	U2R	91.58%	92.48%
	R2L	81.30%	82.20%
J48	***Normal***	94.60%	95.10%
	Probe	95.30%	96.20%
	DoS	87.70%	91.60%
	U2R	95.53%	96.43%
	R2L	83.43%	84.33%
HSFEBM	***Normal***	95.50%	96.40%
	Probe	95.60%	96.50%
	DoS	95.10%	96.00%
	U2R	96.32%	97.22%
	R2L	79.67%	83.35%

The proposed Ensemble Class based Classification outperforms the other three classifiers of a different family, according to the results. the boosting ensemble focused excessively on the minority class. Based on the results in this step, it suggested that base classifiers could be used to improve the performance of imbalanced multiclass data. The best classifier performance using a single classifier produced better class-based classification accuracy as given in the above Table 4.

V. CONCLUSION

Multiclass imbalance, as noted in the previous section, is still an issue in real-world data mining and machine learning when data is severely affected by a large imbalance ratio between samples where one or more classes have fewer samples while the other classes have too many samples. The hybrid classifier was designed in this work using HSFEBM can be customized to produce a new classifier structure used to build and test several design combinations in order to determine the optimal design. The results reported in the previous section clearly show that hybrid ensemble classifiers outperform single classifiers. While the hybrid ensemble classifiers examined in this study performed nearly identically. If the data isn't changed, the ensemble classifier can outperform any single classifier. The following concerns connected to AI-based techniques in ID will require extensive research in the future.

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