International Journal of Innovative Technology and Interdisciplinary Sciences
https://journals.tultech.eu/index.php/ijitis
ISSN: 2613-7305
Volume 7, Issue 3
DOI: https://doi.org/10.15157/ijitis.2024.7.3.80-97
Received: 05.06.2024 ; Revised: 21.08.2024 ; Accepted: 03.09.2024

Research Article

An application with meta-methods (MetaRF) based on random forest classifier

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Abstract

Meta classifiers are an area of intense study in the field of machine learning to improve classification performance. On the other hand, Random Forest is an important classifier in terms of providing fast and effective results. In this study, a meta-ensemble classifier called MetaRF based on the Random Forest basic learner is presented to use and combine the advantages of meta classifiers. For experimental results, the Random Forest base learner and eight meta-learners (AdaBoost, MultiBoostAB, Bagging, Stacking, UltraBoost, FeatureselectedClassifier, RandomSubSpace, FilteredClassifier) were used for ensemble classification on five datasets from the UCI Machine Learning Repository. Experimental results are promising in terms of accuracy rates, precision, recall and F-measure values. The method designed in the study is recommended to be used in machine learning studies and meta-classifier applications.

Keywords: *Machine Learning; Meta Methods; MetaRF; Random Forest*

INTRODUCTION

The Classification is one of the most studied machine learning topics. Classification algorithms are based on the approach of learning the model from labeled training examples and then using this learning to classify new examples of the dataset. Classification analysis is widely used in the real world. Over the years, researchers have developed numerous algorithms that have highly useful applications in many fields such as education, engineering, healthcare, and finance. A single algorithm cannot optimally learn all the information in the data. For this reason, the question of which algorithm should be used among the existing algorithms for the model is of great importance [1, 2].

Ensemble classifiers are systems that aim to combine new examples with the individual decisions of a set of classifiers through weighted or unweighted voting. These systems appear as meta-classifier algorithms that focus on achieving better classification performance by using multiple models. In recent years, ensemble learning (or meta classifier) has been widely used in a wide variety of subjects such as image classification,

pattern recognition, remote sensing, text mining, and deep learning due to its powerful results.

Khan et al. (2020) [3] in their study analyzing the problem of classification algorithm proposal based on meta-learning, presented a comprehensive overview of the important dimensions of meta-learning for classifier selection and answered the six research questions formulated on three important dimensions such as meta-features, meta-learner and meta-target. In the study, they summarized and critically analyzed relevant studies in the literature.

Zheng et al. (2020) [4] proposed a new and effective unified meta-learning-based fake credit card detection model. This new meta-learning-based classifier is designed as a deep Ktuplet network. This network generalizes the triplet network to allow joint comparison with K-negative samples in each mini-group. Experimental results have shown that the proposed approach achieves significantly higher performance compared to state-of-the-art approaches.

Nhu et al. (2020) [5] presented an application of Random Forest and its ensembles for shallow landslide susceptibility mapping in a semi-arid region of Iran. The study was carried out in three stages. First of all, shallow landslide inventory maps were prepared for the Bijar District of Iran. Shallow landslide susceptibility mapping was then completed using machine learning ensemble models including Random Forest and three meta-classifiers. Finally, landslide susceptibility maps were verified. The proposed Rotation Forest-Random Forest (RF-RAF) with an overall accuracy and prediction power of 94.4% and 93.2% respectively performed better than Bagging-Random Forest (BA-RAF), Random Subspace-Random Forest (RS-RAF) and Random Forest (RAF) models.

Achakzai and Juan (2022) [6] developed a meta-classifier to detect financial fraud by combining various independent classifiers. The results revealed that the meta-classifiers developed in the study can outperform the best independent classifiers in detecting fraudulent companies. Researchers mentioned that the developed methodology can be copied and used in other studies related to forecasting.

Ravi et al. (2022) [7] proposed a large-scale learning method for COVID-19 classification with a stacked ensemble meta-classifier and a deep learning-based feature fusion approach. In the study, they used a stacked ensemble meta-classifier-based approach for classification. This is a two-step approach. Random forest and support vector machine (SVM) were applied for prediction in the first stage and fed in the second stage. The second stage included the logistic regression classifier, which classified the CT and CXR data sample as COVID-19 or non-COVID-19. The performance of the proposed model was compared with various existing CNN-based pre-trained models and it was concluded that it performed better than existing methods.

Kumar and Verma (2022) [8] designed a hybrid algorithm based on the stacking approach for classification of network traffic. The hybrid classification algorithm integrates

SVM with the KNN classification algorithm. The proposed model achieved an accuracy of up to 97.18%, while the precision and recall values were obtained as 95 and 94%, respectively.

Nasir et al. (2022) [9] evaluated various artificial intelligence algorithms to process water quality data and predict water quality as accurately as possible. Various machine learning classifiers and their stacking ensemble models were used to classify WQ data through Water Quality Index (WQI). Classifiers examined included Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), Decision Tree (DT), CATBoost, XGBoost and Multilayer Perceptron (MLP). The findings revealed that the CATBoost model offered the most accurate classifier, with 94.51 percent. Moreover, after applying the stacking ensemble models with all classifiers, the accuracy reached 100% in various meta-classifiers. In addition, CATBoost achieved the highest accuracy as the primary gradient-boosting algorithm and meta-classifier.

Kumari and Suresh's (2023) [10] research is a more accurate prediction of heart disease using an ensemble stacking model based on mixing heterogeneous classifiers. The research consists of two main parts. The first is the analysis for the selection of the best meta-classifier with a different set of base classifiers. The second is prediction using an ensemble framework. Experimental results show that ensemble techniques provide 90.16% better accuracy for testing the dataset.

Ensemble classifiers consist of the union of multiple base (weak) learners. Decision tree types such as CART, J48, REPTree are often used as base learners. Random Forest, introduced by Breiman [11], is an extension of the bagging method. It is suitable for classification problems because it is fast and sensitive. In Random Forest, random selection of features to split each node results in significant performance over error rates. In this study, a meta-ensemble method using Random Forest as the base learner is discussed. A comparative analysis of the Random Forest base learner and eight meta-ensemble learners on five datasets in the UCI Machine was made on four performance criteria (accuracy, precision, recall, and F-measure).

MATERIAL AND METHOD

In the analyses performed in the study, the Random Forest algorithm was chosen as the basic classifier for all data sets. 13 meta classifiers under the title 'weka' were used in the modeling using the WEKA program. 10-fold cross-validation was applied to all datasets to obtain reliable results. Figure 1 provides an overview of the experimental system.

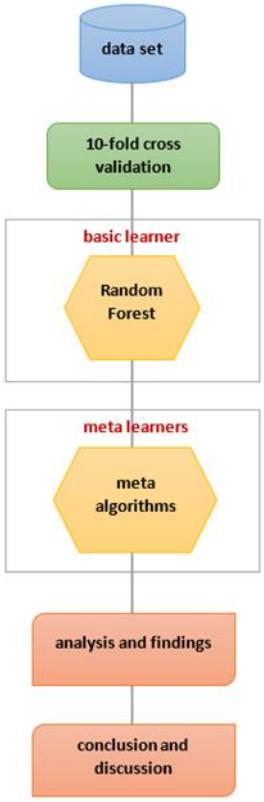

Figure 1. Overview of the proposed system

Data Sets

Five datasets for classification applications from the UCI Machine Learning Repository were used in the study. These datasets contain real-world data. Table 1 shows the number of observations in the data set and the number of features and number of classes in which each described observation is evaluated.

Table 1. Characteristics of the data sets used in the study

Data sets	Number of instances	Number of features	Number of classes
blood	748	5	2
dermatology	366	35	6
ionosphere	351	35	2
liver	345	7	2
glass	214	10	7

Meta Classifiers

Meta-classification refers to analyses made by combining more than one classifier. Thus, it is thought that stronger predictions will be obtained [12].

Meta methods are based on a study by Dasarathy and Sheela (1979) [13]. The work is based on the idea of splitting the feature space using multiple classifiers. Schapire, in his study in 1990 [14], showed that ensemble learning methods could be more powerful for classification problems. In the following years, studies on meta-classifiers have diversified.

In the study titled "Meta Classification Algorithms - An Application with Weka", 13 different classifiers under the title of weka were analyzed for 20 different data sets in order to compare the performance results of meta-classifiers [15]. In study, the J48 algorithm was chosen as the subclassifier. Performance metrics showing model performances for each data set were calculated taking into account the complexity matrices and the results were discussed comparatively. At the end of the study, the algorithms with the best accuracy value were discussed as the subject of this study, and these algorithms are mentioned in the rest of the section.

AdaBoost

AdaBoost is one of the most used boosting algorithms. It was first proposed by Freund and Schapire (1997) [16]. With AdaBoost, many of the practical difficulties of previous boosting algorithms have been solved [17]. For this reason, it is preferred over other boosting methods due to its features such as high prediction speed, low memory usage, and easy applicability. It is considered the first boosting algorithm and won the Gödel award, one of the important awards in the computer world [18].

The working steps of the AdaBoost algorithm are based on the logic of creating a weak classifier from each feature and obtaining an ensemble of these weak classifiers. The decision limits of weak classifiers are found by taking the weighted average of negative and positive examples for each feature. A new strong classifier is created with the help of weak classifiers with the lowest error rate. Thus, the features of weak classifiers that are not included in the strong classifier are deleted [19].

MultiBoostingAB

The MultiBoosting (MB) method is an extension of the AdaBoost technique, which is very successful in creating decision committees. MB can be described as combining AdaBoost with wagging. With this method, both AdaBoost's high bias and variance reduction can be overcome by taking advantage of the superior variance reduction property of shaking. This method offers more advantages over AdaBoost because it is suitable for parallel execution [20].

Bagging

The bagging method was suggested by Breiman (1996) [21]. In this method, a combined estimator is obtained by creating multiple versions of an estimator [22]. The method starts by taking the existing training set as input, and from there, new training sets are created, and the base classifier is repeated and trained. The learner trained for new training sets is

tried on a test set and the results are calculated by taking the average. The main purpose of bagging is to identify differences and increase the final classification success by producing new data sets.

The basic learner in bagging is decision trees. Decision trees are easy to create and decisions are quick. Firstly, a tree structure is created for the decision tree. There are classes on the leaves of the tree. The nodes going from the trunk to the leaves are comparisons. To create the tree structure, entropy values are calculated for each feature in the data set. Base learners do not have to be decision trees; any learning algorithm can be chosen.

Stacking

The stacking algorithm trains multiple classification models with the same training set by combining them through a meta-classifier, resulting in multiple classification models. In the stacking algorithm, the outputs of the sub-models are taken as input. The algorithm tries to learn how best to combine the input predictions for a good prediction, and the model eventually sends the output it obtains as input to the meta-classifier. The resulting output is determined as a class label [23].

In the stacking algorithm, n different subsets of the training data set are created. Stratified sampling with replacement is used here, where the relative proportion of different classes in the subsets is preserved. For each classifier, a meta-classifier is created by assigning a weight proportional to its performance [24]. There are no rules for choosing the meta-classifier.

UltraBoost

UltraBoost (UB) is a meta-classifier that works by using a different classifier at each stage. It is named UB because it was developed at the Ultrasound Research Laboratory at the University of Pennsylvania. Typical use of the method includes two or three stages, each with a different classifier. By default, UB uses naive Bayes and logistic regression [25, 26].

Attribute Selected Classifier

In the AttributeSelectedClassifier (ASC) method, the size of the training and test data is reduced by feature selection before starting the classification analysis. To do this, first a subset of the basic training set is created to be compared. Next, a new candidate subset is created. If this cluster gives better results as a result of the evaluation, it is selected as the best subset. These steps continue until the termination condition is met. The classification process is completed with the help of a pre-selected classifier with a new subset having a reduced number of features.

The ASC method, like other methods, has various parameters. The choice of 'evaluator' and 'search' algorithms among these parameters directly affects feature selection. The evaluator sets the feature evaluator to use. CfsSubsetEval is the most commonly used method. Search is the selection of the search method. BestFirst is the most widely used

search algorithm. Both features are used in the feature selection stage before applying the classifier.

Random Sub Space

RandomSubSpace (RSS) method is an algorithm first implemented by Ho (1998) [27]. In this method, a community is created and the cycles are repeated. In each iteration, the input selects a few features from the feature space and the classifier is trained with a subset of the features. In the RSS algorithm, new data sets are created with different features of a learner and training set. New training sets are derived by deleting some dimensions of the initial training set. For example, from a data set with m features, new data sets with n features (n<m) are randomly selected. Then, the determined base learner is trained with the newly created training sets. The learner's decision for the test set is determined by combining the decisions made by the learners obtained with new data sets [27, 28].

RSS is a parallel learning algorithm. In the method, the creation of each decision tree is independent. The difference of this model from other techniques is that it uses different variables on an entity space [29]. One of the disadvantages of the RSS model is the overfitting problem [27].

Filtered Classifier

In the FilteredClassifier (FC) method, the training data is classified by passing it through a random filter. The structure of both the classifier and the filter is based solely on the training data. Test data is processed by the filter without changing its structure. If the filter (or classifier) cannot cope with the presence of unequal sample weights or feature weights, the samples are resampled by changing the weights before being passed to the filter (or classifier).

Random Forest (RF)

In this algorithm, developed by Breiman in 2001 [11], the aim of the classifier is to combine the decisions of many trees, each trained in different training sets, instead of producing a single decision tree. Random Forest (RF) uses the CART algorithm to create a decision tree. The nodes and branches in the decision tree are created according to the features of this algorithm. When creating decision trees and determining the features at each level, the feature is first determined by making some calculations in all trees, then the features in other trees are combined and the most used feature is selected. The selected feature is included in the tree and the same processes are repeated at other levels. Figure 2 explains the working system of the RF algorithm.

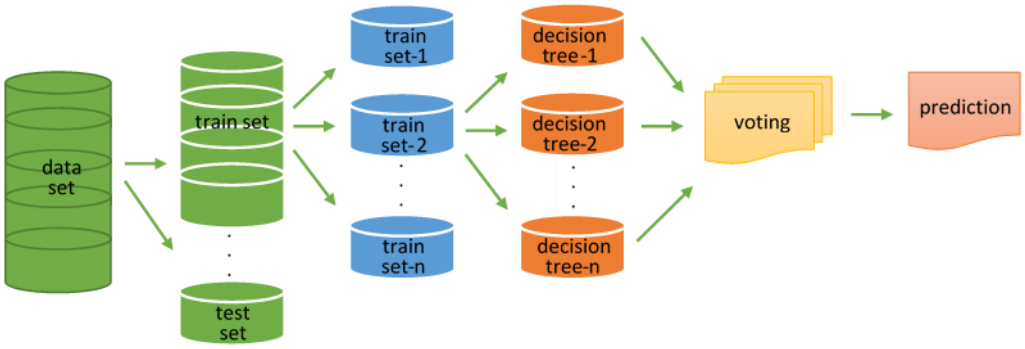

Figure 2. Working principle of Random Forest algorithm

RF is used for both classification and regression. The RF method uses the Gini algorithm, which measures the suitability of class variables, as the division criterion when creating decision trees. RF method:

- Determining the variables to be used in classification,

- Detecting interactions between variables,

- Identification of missing data,

- Determination of outliers' and

- It is used for clustering analysis.

In case there are many variables in the data set, it is useful to make more effective predictions by reducing the number of variables and reducing the model based on their importance levels. Since the RF method has a large number of trees, the trees cannot be seen visually and this prevents the calculation of a certain confidence interval. For this reason, it is not possible to talk about a value for the confidence interval of the classification process. On the other hand, since the bootstrap technique in the RF algorithm generalizes the classification, there is no need for a confidence interval.

Meta-Classifiers Based on RF Algorithm (MetaRF)

Meta-algorithms are structures that turn classifiers into more powerful learners. As a working principle, it combines a meta tutorial with one (or sometimes more) classifiers. In this study, MetaRF is considered as the general expression of a hybrid approach that supports all meta-algorithms with the Random Forest algorithm.

In this section, the description of the proposed algorithm is mentioned. First, a classification problem regarding training data is expressed in Equation 1:

$$T = \{(x_1, y_1), \dots, (x_k, y_k)\} \in (R^N x\, y)^k \quad (1)$$

Here is $x_i \in R^N$, $y_i \in y = \{1, -1\}$, i= 1, …, k. The architecture of MetaRF classifiers is simply shown in Figure 3. It can be seen from the figure that the multilayer architecture of MetaRF classifiers includes an input layer, hidden layers and an output layer. Then, in the k'th layers, there are n RFs that serve as new features for the next layer. Here, how to measure the importance of each feature and how to choose the most appropriate classifiers for the kth layers are two basic issues that will directly affect the performance of the model. With the meta-classifier mechanism as the layers increase, a better data set can be obtained for classification compared to basic learning algorithms. Since the output of each layer is considered as new training data for the next layer, the training data of the kth layers is expressed by Equation 2:

$$T^k = \{([f_1^{l-1}(f_1^{l-2} \dots f_1^1)(x_1), \dots, f_n^{l-1}(f_n^{l-2} \dots f_n^1)(x_1)], y_1), \dots, ([f_1^{l-1}(f_1^{l-2} \dots f_1^1)(x_k), \dots, \in (R^N x\, y)^k \quad (2)$$

As the last step, RF is applied to create the decision function by training the extracted feature vector in hidden layers.

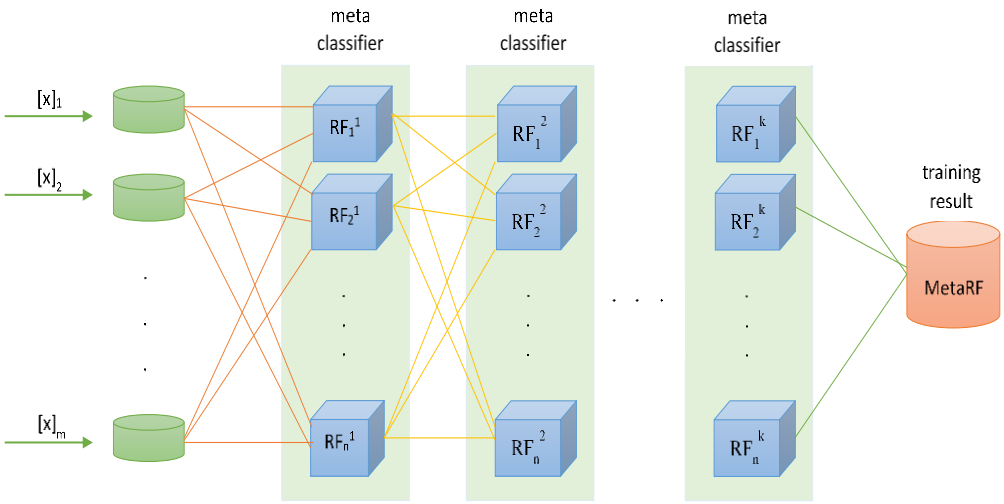

Figure 3. Working principle of Random Forest algorithm

10-fold Cross Validation

Cross-validation is a technique used in model selection. In this technique, the data set is divided into k subgroups. One group is used as the test set and the remaining groups are used as the training set. This calculation repeats k times. Figure 4 shows the operation of the method [30].

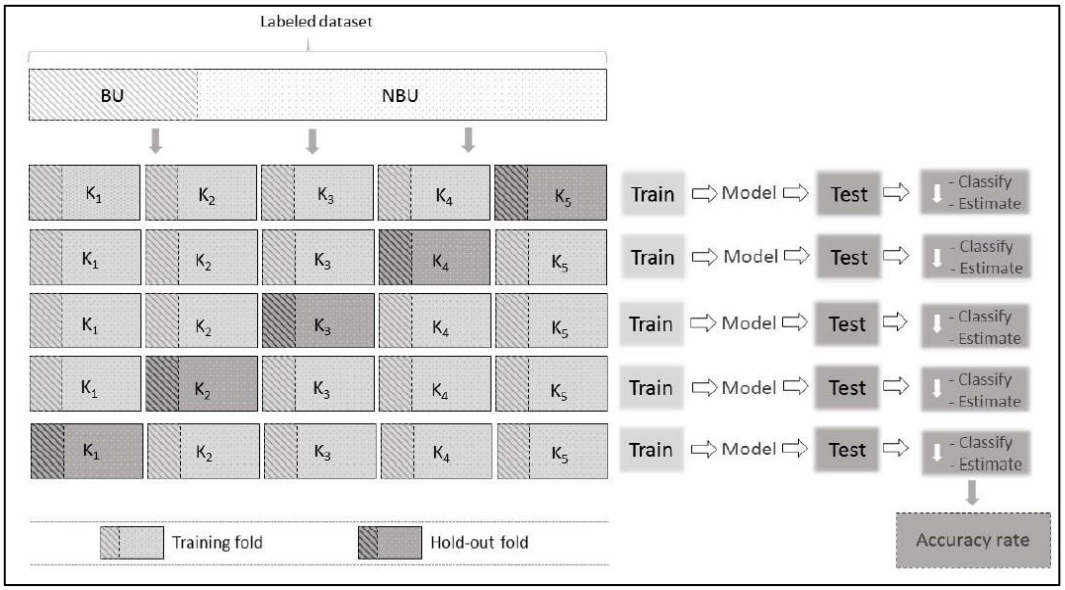

Figure 4. k-fold (5-fold) cross-validation scheme

Performance Metrics

Accuracy

Accuracy is a measurement obtained by dividing the number of correctly classified observations by the total number of samples (Equation 3).

$$ACC = \frac{(TP + TN)}{(TP + TN + FN + FP)} \tag{3}$$

Precision

The concept of precision is defined as the ratio of the number of positive samples with class 1 to the number of samples with class 1 (Equation 4).

$$PRE = \frac{TP}{(TP + FP)} \tag{4}$$

Recall

It is the ratio of the number of correctly classified positive observations to the total number of positive observations (Equation 5).

$$REC = \frac{TP}{(TP + FN)} \tag{5}$$

F-Measure

It is the harmonic mean of precision and sensitivity (Equation 6).

$$F = \frac{2 * PRE * REC}{PRE + REC} \tag{6}$$

RESULTS

In the study titled "Meta Classification Algorithms-An Application with Weka" conducted by Durmuş et al., the performance results of meta classifiers were compared. 15 different meta classifiers under the title of 'weka' were analyzed for 20 different data sets taken from the UCI Machine Learning Respository database. The J48 algorithm was used as the base learner. The performance results obtained from this study are given in Table 2 (Durmuş et al., 2023). When the results are discussed, it is seen that 8 out of 13 methods have the highest performance (Figure 5).

Table 2. Results obtained from the study titled "Meta Classification Algorithms-An Application with Weka"

data set	algorithm
ecoli	MultiBoostAB
post-operative patient	Stacking
lymphography	MultiBoostAB
car evaluation	AdaBoost
connect-4	MultiBoostAB
balance scale	MultiBoostAB
dermatology	MultiBoostAB
skin segmentation	AdaBoost
user knowledge modeling	AdaBoost/MultiBoostAB
blood transfusion service center	Bagging
adult	FilteredClassifier
haberman's survival	Bagging
indian liver patient	Stacking/UltraBoost
breast-cancer	UltraBoost
tic-tac-toe endgame	AdaBoost
diabetes	AttributeSelectedClassifier
ionosphere	RandomSubSpace
spambase	AdaBoost
liver disorders	AdaBoost
credit approval	Bagging

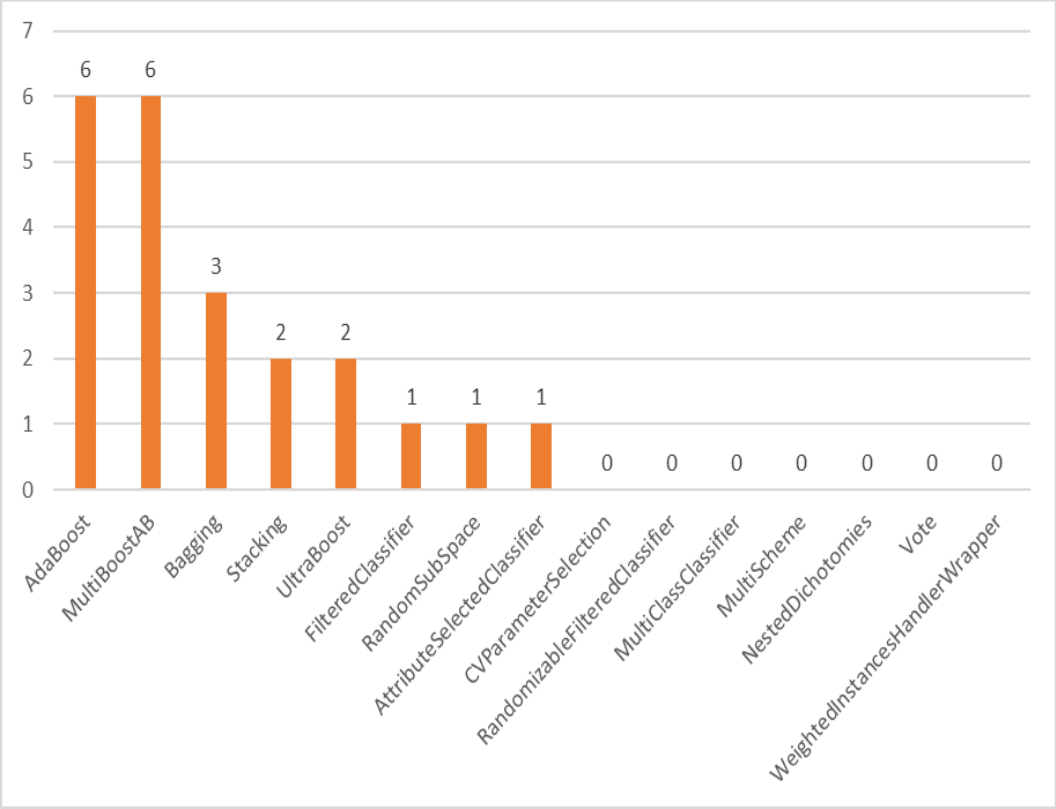

Figure 5. Performance distribution of algorithms for the study titled "Meta Classification Algorithms-An Application with Weka"

In this study, AdaBoost, MultiBoostAB, Bagging, Stacking, UltraBoost, AttributeSelectedClassifier, RandomSubSpace, FilteredClassifier algorithms are focused on based on the results obtained from the study titled "Meta Classification Algorithms-An Application with Weka". These algorithms have the best accuracy value for the data sets in the previous application. Random Forest algorithm is considered as the subject of this study as the base learner. Random Forest algorithm can be considered as the most widely known meta algorithm. Based on this idea, it is aimed to strengthen meta classifiers with a meta base learner in this study. These methods whose base learner is Random Forest are referred to as 'metaRF' in the study. Algorithm performances are evaluated for 5 different data sets and the results are presented in Tables 3-6.

Table 3 presents the accuracy values obtained with the metaRF classifier for the studied datasets. While results successful over 90% were obtained for the dermatology and ionosphere data sets, the success rate in other data sets is over 74%. As can be seen from the results, high performance results are obtained with the MetaRF classifier.

Table 3. Accuracy value results for the MetaRF classifier

accuracy	blood	dermatology	ionosphere	liver	glass
AdaBoost	72,995	95,628	93,732	72,464	75,001
MultiBoostAB	75	-	-	-	-
Bagging	74,332	96,721	94,017	74,493	74,766
Stacking	69,652	95,628	92,593	57,971	74,766
UltraBoost	72,059	96,175	93,164	74,783	76,636
AttributeSelectedClassifier	75,401	96,175	92,878	55,942	73,365
RandomSubSpace	76,872	95,082	93,732	68,406	78,037
FilteredClassifier	74,465	96,448	90,883	56,232	64,953

Table 4-6 show the precision, recall and F-measure values for all datasets, respectively. These values give similar results when compared with Table 3.

Table 4. Precision value results for the MetaRF classifier

precision	blood	dermatology	ionosphere	liver	glass
AdaBoost	0,707	0,956	0,938	0,722	0,754
MultiBoostAB	0,724	-	-	-	-
Bagging	0,72	0,967	0,942	0,743	0,736
Stacking	0,677	0,956	0,926	-	0,74
UltraBoost	0,697	0,962	0,932	0,746	0,763
AttributeSelected Classifier	0,718	0,962	0,929	0,565	0,71
RandomSubSpace	0,729	0,951	0,937	0,684	0,777
FilteredClassifier	0,667	0,964	0,911	0,535	0,627

Table 5. Recall value results for the MetaRF classifier

recall	blood	dermatology	ionosphere	liver	glass
AdaBoost	0,73	0,956	0,937	0,725	0,757
MultiBoostAB	0,75	-	-	-	-
Bagging	0,743	0,967	0,94	0,745	0,748
Stacking	0,697	0,956	0,926	0,58	0,748
UltraBoost	0,721	0,962	0,932	0,748	0,766
FeatureselectedClassifier	0,754	0,962	0,929	0,559	0,734
RandomSubSpace	0,769	0,951	0,937	0,684	0,78
FilteredClassifier	0,745	0,964	0,909	0,562	0,65

Table 6. F-measure value results for the MetaRF classifier

F-measure	blood	dermatology	ionosphere	liver	glass
AdaBoost	0,716	0,956	0,937	0,721	0,746
MultiBoostAB	0,732	-	-	-	-
Bagging	0,728	0,967	0,939	0,742	0,732
Stacking	0,685	0,956	0,926	-	0,741
UltraBoost	0,706	0,961	0,931	0,745	0,753
FeatureselectedClassifier	0,725	0,962	0,928	0,561	0,717
RandomSubSpace	0,72	0,951	0,937	0,67	0,761
FilteredClassifier	0,678	0,964	0,907	0,522	0,627

In addition to these tables, graphs are given in Figure 6-9 to comparatively show the effects of classifiers and data sets.

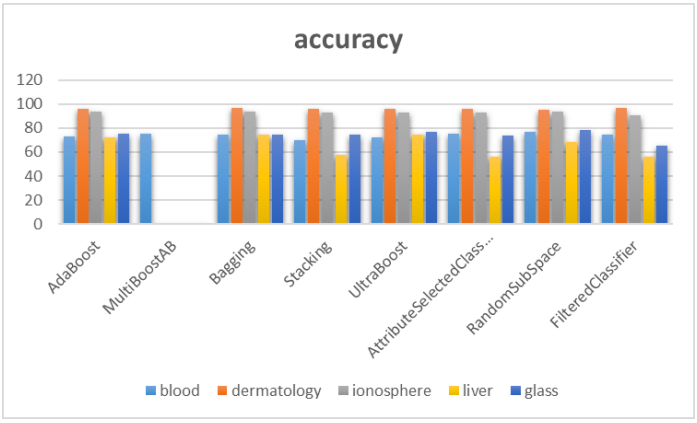

Figure 6. Accuracy value results for the MetaRF classifier

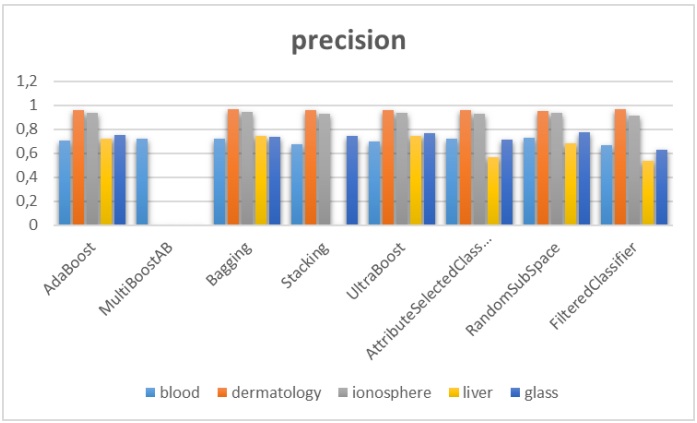

Figure 7. Precision value results for the MetaRF classifier

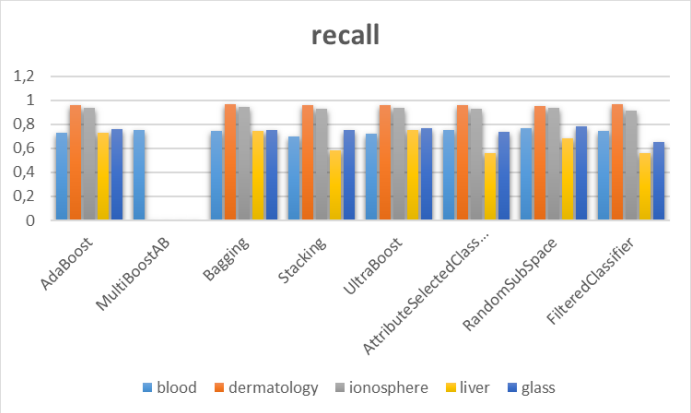

Figure 8. Recall value results for the MetaRF classifier

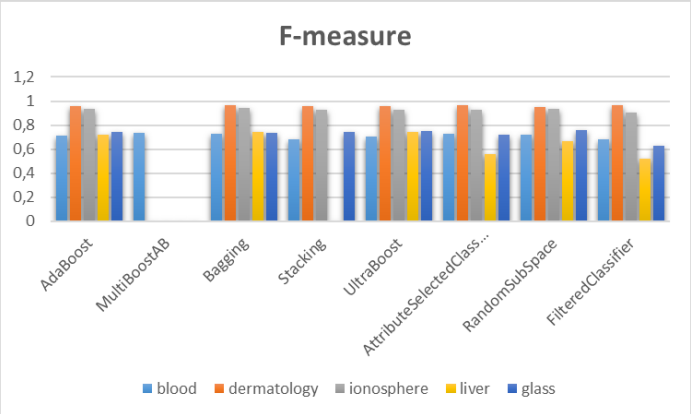

Figure 9. F-measure value results for the MetaRF classifier

CONCLUSION

Nowadays, studies on meta-classifiers are becoming increasingly widespread due to their effective use and high performance in various fields such as machine learning and pattern recognition. In this study, meta-methods (MetaRF), whose base classifier is a meta-classifier (Random Forest), are discussed to classify data. In order to work with meta-classifiers, it is necessary to have knowledge about single classifiers. Because single classifiers directly affect meta-classifiers. The disadvantages of meta-classifiers arise from the disadvantages of single classifiers. Therefore, it is important to choose the right base classifier. Calculations with meta-classifiers require more space and time. However, working with meta-classifiers provides more efficient results by using the hybrid advantages of the algorithms.

In this study, an integrated meta method was implemented using the Random Forest algorithm, which has been proven to have high performance in the literature many times and has a wide application area. Since this method exhibits a two-layer learning, it models

with a more complex structure than other basic learners. In studies conducted with meta algorithms, single classifier is usually selected. In addition, algorithms selected as 'default' are used in parameter selection. This study uses the Random Forest algorithm as the basic learner, unlike other studies. The focus of the study is that the Random Forest algorithm acts as a meta classifier. Thus, it was investigated whether the Random Forest algorithm strengthens the meta classifiers by providing multi-dimensional learning.

In our study, 8 models called MetaRF were created for each dataset. The results obtained show that the overall success of the method is over 74%, and especially for dermatology and ionosphere datasets, over 90% successful results were obtained. These results show that it may be appropriate to choose the Random Forest algorithm as the base learner. No general comment could be made on which of the meta classifiers considered in the study is more successful. The results show that a different algorithm is successful for each dataset. It is thought that it would be appropriate to select meta methods by conducting several experiments in accordance with the data set in the studies to be conducted.

In future studies; i) Repeating the analyses with different data sets and discussing the results comparatively will reveal the data sets where the metaRF method is effective. Thus, stronger classification results can be obtained with more effective models. ii) Hybridizing meta classifiers with other algorithms can be another study. It is known that there are studies on hybrid meta methods in the literature. By selecting the Random Forest algorithm as the base learner, these hybrid methods can be provided with multi-dimensional learning. iii) In order to improve the classification, weighting of the classifiers can be done for the base and meta learners. When we look at the working principles of the algorithms, it is seen that the decision classes or training classes are selected randomly. Randomness can be eliminated or reduced by applying data weighting under appropriate conditions for classification. Thus, more effective results can be obtained.

CONFLICT OF INTERESTS

The authors confirm that there is no conflict of interest regarding this publication.

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