CLASSIFICATION OF CORONARY ARTERY DISEASES USING STACKING ENSEMBLE LEARNING METHOD

A. Doganer, and M. Kirisci

Abstract— *Aim:* Coronary artery disease is one of the most fatal diseases in the the society. Early diagnosis and treatment of coronary artery disease plays an important role in reducing the number of deaths. In this study, it is aimed to classify coronary artery disease by Stacking based ensemble learning methods.

Material and Methods: The study was obtained from the data of 244 patients with coronary artery disease and 116 individuals without coronary artery disease who were treated in Kahramanmaras Sutcu Imam University Health Practice and Research Hospital. The data were obtained retrospectively. The data set consists of 15 predictor variables and 1 dependent variable. In the classification process, Naive Bayes, Sequential Minimal Optimization, Random Forest classifiers and Stacking ensemble learning method were applied. A 10-fold cross validation method was applied to the model. Accuracy, sensitivity, specificity, F-measure and AUC metrics were applied to evaluate the performance of classifiers. The most essential variables in predicting coronary artery disease have been determined.

Results: ACC = 0.774, SEN = 0.888, SPE = 0.719, F = 0.718 and AUC = 0.913 values were obtained with the Naive Bayes classifier in the study. ACC = 0.883, SEN = 0.733, SPE = 0.955, F = 0.802 and AUC = 0.844 were obtained with the SMO classifier. ACC = 0.908, SEN = 0.853, SPE = 0.934, F = 0.857 and AUC = 0.957 were obtained with Random Forest classifier. ACC = 0.933, SEN = 0.905, SPE = 0.946, F = 0.897 and AUC = 0.959 values were obtained with the stacking ensemble learning method. BUN, MPV, Age, AST and Monocyte variables were determined as the most essential factors in the classification of coronary artery disease, respectively.

Conclusion: Stacking ensemble learning method provided the highest accuracy performance in the classification of coronary artery disease. Stacking ensemble learning method gives successful results in the classification of coronary artery diseases.

Keywords— *Coronary Artery Disease, Stacking Ensemble Learning Methods, Artificial Intelligence, Meta Classifier.*

1. INTRODUCTION

CORONARY artery diseases are among the most fatal diseases in the world [1]. Coronary artery disease is a cardiovascular disease expressed by the occlusion or narrowing of the vessels due to the presence of plaques in the arteries that cause atherosclerosis [2]. Coronary artery disease is stated as the cause of one out of every 7 deaths in the United States [3]. Coronary artery disease is among the diseases with a serious risk of death in both developing and developed countries [4]. Therefore, developments in the early diagnosis and treatment of coronary artery disease are substantial. Early diagnosis of coronary artery disease prevents possible deaths. Coronary angiography and visualisation techniques are used for the detection of coronary artery disease. Coronary angiography is a diagnostic method that is difficult to perform and includes certain risks [5]. Machine learning methods have made a powerful alternative in the diagnosis of coronary artery diseases.

Machine learning methods have been used frequently in the early diagnosis of diseases in recent years. Machine learning methods, which provide a successful classification performance, make an important contribution to the early diagnosis of heart diseases. Machine learning methods and applications related to artificial intelligence in the early diagnosis of coronary artery disease have attracted the attention of many researchers. Researchers have suggested some models for early diagnosis of coronary artery disease. Poss et al. (2018) used machine learning methods to reveal the biomarkers of coronary artery diseases [6]. Verma et al. (2016) proposed a hybrid model consisting of machine learning methods for the diagnosis of coronary artery disease [7]. Zheng et al. (2011) used machine learning methods in their studies to perform coronary artery segmentation [8]. Nikan et al. (2017) compared the performances of 3 different classification models to predict coronary artery risk [9]. Artificial intelligence methods provide successful results for early diagnosis of diseases using ECG signals. Acharya et al. (2017) proposed a model for the automatic detection of coronary artery disease using convolutional neural networks (CNN) and ECG signals [10].

Many researchers have tried to detect coronary artery disease by applying different models. Some classifiers do not provide sufficient performance for classifying coronary artery diseases. In this study, it is aimed to develop a model for the early diagnosis of coronary artery diseases with the Stacking ensemble learning method. With the Stacking ensemble learning method, it is aimed to achieve high accuracy performance in the detection of coronary artery diseases. In the model, the performances of Naive Bayes, Sequential Minimal Optimization, Random Forest classifiers and Stacking ensemble learning methods are compared.

2. MATERIAL AND METHODS

The data set of the study consists of patient records of the Cardiovascular Surgery Service of Kahramanmaras Sutcu

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Imam University Health Practice and Research Hospital. The data were obtained retrospectively. The study includes data on patients with coronary artery disease and individuals without coronary artery disease. Permission was obtained from the clinical research ethics committee of Kahramanmaras Sutcu Imam University to conduct the study (Ethics Committee Approval No: 2019/21 Decision No: 13). The number of samples in the study was determined by power analysis. With α: 0.05 first type error level, B: 0.20 second type error level and 0.80 test power, taking into account the accuracy estimation value 91.2% in the reference study [11], a total of 360 cases were planned to be included in two groups for a 5% deviation level. The data set consists of a total of 365 data, including 249 patients with coronary artery disease and 116 individuals without coronary artery disease. The data set consists of 16 variables, including 1 dependent variable and 15 predictor variables. The variables in the data set are shown in Table 1.

TABLE I
FEATURES OF VARIABLES

Variable	Variable Description	Variable Role
Type of Diseases	CABG/ M. Bridge	Output
Gender	Male/Female	Input
Age (Years)	Quantitative	Input
Hemoglobin (HB)	Quantitative	Input
Hematocrit (HCT)	Quantitative	Input
Neutrophil	Quantitative	Input
Lymphocyte	Quantitative	Input
Monocyte	Quantitative	Input
Platelet (PLT)	Quantitative	Input
Mean Platelet Volume (MPV)	Quantitative	Input
Blood Urea Nitrogen (BUN)	Quantitative	Input
Creatinine	Quantitative	Input
Aspartate Aminotransferase (AST)	Quantitative	Input
Alanine Aminotransferase (ALT)	Quantitative	Input
Total Cholesterol	Quantitative	Input
Low Density Lipoprotein (LDL)	Quantitative	Input

Outliers in the dataset are analyzed with the local outlier factor (LOF) algorithm. Data with outliers were excluded from the study [12]. Standardization (Z-transform) process was applied to the quantitative data for the classification process. In the study, the performances of Random Forest classifier (RF), Naive Bayes (NB), Sequential Minimal Optimization (SMO) and stacking ensemble learning methods were compared for the classification of diseases. Individual classification performances of RF, NB and SMO classifiers were evaluated. In addition to individual classification, the RF, NB and SMO classifiers were included in the ensemble model for Stacking ensemble learning method. The Logistic Classifier has been implemented as a meta classifier for the ensemble model. The K fold-10 cross validation method was applied to train the model. Grid search algorithm was used for hyperparameter optimization of classifiers. Weka 3.9.3 (Waikato Environments for Knowledge Analysis) and R 3.3.2 software were used to perform the classification processes.

2.1. Stacking Ensemble Learning Methods

The ensemble learning method has made a powerful alternative to other machine learning methods for classifying data. Ensemble learning methods are machine learning methods based on the principle that by combining the estimates of more than one classifier, more reliable and more accurate estimates can be procured than the estimates of a single classifier [13]. In order to increase performance in ensemble learning methods, appropriate defragmentation method and appropriate classifiers should be included in the model. Stacking ensemble learning method is one of the ensemble learning methods that can provide high classification performance. The stacking ensemble learning method includes more than one classifier to the model. It transmits the estimate of each classifier in the model to a meta classifier. The meta classifier produces the ensemble estimate by processing the estimates from the classifiers in the model as input [14]. In the study, Random Forest (RF), Naive Bayes (NB) and Sequential Minimal Optimization (SMO) classifiers were included in the Stacking ensemble learning model. Logistic classifier ranks as a meta classifier in the study.

2.2. Random Forest

Random Forest is a classifier consisting of many decision trees. The Random forest classifier developed by Breiman, different subsets created by bootstrap sampling method from the data set are trained with each decision tree [15]. Classification is initiated by determining the number of decision trees and the number of variables that will perform the division in the model. In the random forest classifier, the decision is made by "majority voting" method among the predictions of each decision tree. The random forest classifier, which provides strong and high performance, is also highly resistant to overfitting problem [16-17].

2.3. Naive Bayes

Naive Bayes, a strong and plain classifier, classifies on the basis that all variables are independent [18]. The Naive Bayes classifier, which takes its theoretical basis from the Bayes theorem, is capable of fast learning. The Naive Bayes classifier, which classifies using probabilistic methods and makes use of prior probabilities. It can provide high performance for large data sizes and for classification of categorical data [19-20].

2.4. Sequential Minimal Optimization

The Sequential Minimal Optimization (SMO) classifier which uses analytical quadratic programming techniques, is capable of solving optimization problems quickly. The SMO classifier, which is basically based on the support vector machine classifier, was developed by Platt. The classifier constantly updates the support vector machine with iterative operations [21]. Being a powerful classifier, SMO can provide high performance in classification processes [22]. Accuracy, sensitivity, specificity, F score and ROC Area metrics were obtained to evaluate the performance of Stacking ensemble learning method with RF, NB and SMO classifiers. These metrics are obtained based on the information in Table II.

TABLE II
CONFUSION MATRIX

		Actual		
		Positive	**Negative**	**Total**
Predicted	**Positive**	(TP)True Positive	(FP) False Positive	TP+FP
	Negative	(FN) False Negative	(TN) True Negative	FN+TN
	Total	TP+FN	FP+TN	TP+FP+TN+FN

Sensitivity: True Positive/ True Positive+False Negative
Specificity: True Negative/True Negative+False Positive
Accuracy: TP+TN / TP+FP+TN+FN
F-Score: (2*TP)/ (2*TP+FP+FN)

3. RESULTS

In the study, outlier analyses were carried out within the data set. Outliers were detected in the data of 5 patients in the patient group. Data on 5 patients were excluded from the study. The data of 360 individuals including 244 coronary artery patient data and 116 non-coronary artery disease data were included in the study. 31.8% of the patients were women and 68.2% were men. The mean age of the patients is 58.35 ± 11.31.

The performances of NB, RF, SMO and Stacking ensemble learning methods were compared for classification of individuals with and without coronary artery disease. The performances of the classifiers were evaluated in terms of accuracy (ACC), sensitivity (SEN), specificity (SPE), F-Measure (F), and ROC Area (AUC) metrics. ACC = 0.774, SEN = 0.888, SPE = 0.719, F = 0.718 and AUC = 0.913 values were obtained with the Naive Bayes classifier. ACC = 0.883, SEN = 0.733, SPE = 0.955, F = 0.802 and AUC = 0.844 were obtained with the SMO classifier. ACC = 0.908, SEN = 0.853, SPE = 0.934, F = 0.857 and AUC = 0.957 were obtained with Random Forest classifier. ACC = 0.933, SEN = 0.905, SPE = 0.946, F = 0.897 and AUC = 0.959 values were obtained with the stacking ensemble learning method. The performances of the classifiers are shown in Table III.

TABLE III
PERFORMANCE METRICS OF METHODS

	Accuracy	Sensit.	Specif.	F-Measure	ROC Area
Naive Bayes	0.774	0.888	0.719	0.718	0.913
SMO	0.883	0.733	0.955	0.802	0.844
Random Forest	0.908	0.853	0.934	0.857	0.957
Stacking ELM	0.933	0.905	0.946	0.897	0.959

The SMO classifier provided the highest performance in terms of specificity metric. The Stacking ensemble learning method provided the highest performance in terms of accuracy, sensitivity, F-Measure, and ROC Area metrics. Comparison of the performance of classifiers is shown in Figure 1.

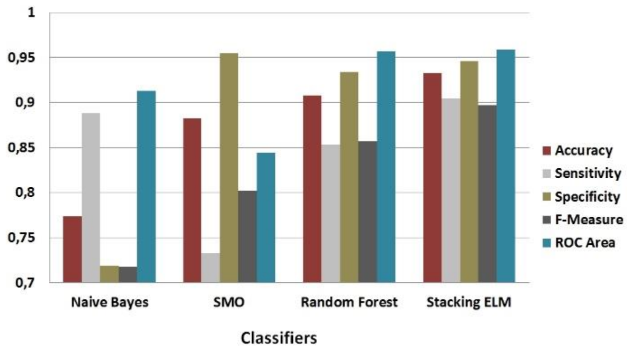

Fig. 1. Performance Metrics of Methods

The significance levels of the predictor variables according to the feature selection methods are shown in figure 2. It has been observed that the variables Bun, Mpv, Age, Ast and Monocyte respectively make the most substantial contribution in the classification of diseases.

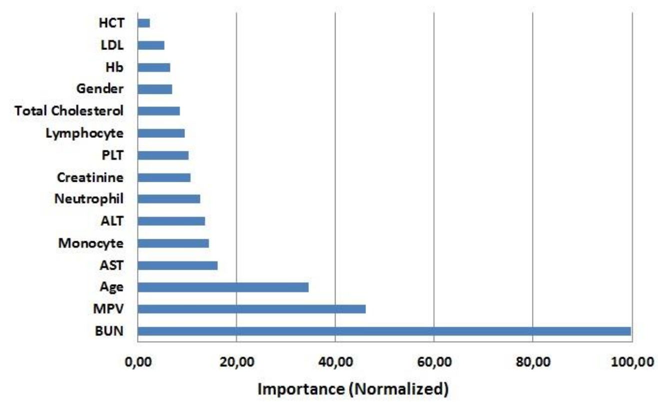

Fig. 2. Importance Value of Predictor Variables

4. DISCUSSION

Machine learning methods can provide successful results for diagnosing and classifying diseases. Early diagnosis of coronary artery diseases is vital in reducing the risk of the disease [23]. Solutions based on clinical applications and imaging methods are available for early diagnosis and classification of coronary artery diseases. However, more practical solutions can be preferred due to the cost and application difficulties of these methods [5]. Machine learning methods can play an effective role in the diagnosis and classification of coronary artery disease and provide practicality for diagnosis.

A great deal of research has been conducted on the early diagnosis of coronary artery diseases with machine learning methods. Different machine learning methods have been applied in many of these studies. Plaiwak (2018) proposed a model in which machine learning methods are used to determine heart disorders with ECG signals. Performance of SVM, KNN, PNN, and RBFNN classifiers were evaluated in the model. SVM classifier provided the highest performance with 90% accuracy [24]. Alizadehsani et al. (2016) applied different functions of some classifiers and SVM classifier in the detection of coronary artery disease in their study. They achieved accuracy performance in the range of approximately 75% to 91% for the 4 functions of SVM proposed in the model [25]. Babaoglu et al. (2010) aimed to increase the performance of SVM classifier in classifying coronary artery diseases with principal component analysis. It was determined that principal components analysis increased the SVM classification performance from 76.67% to 79.71% [26].

Naive Bayes method is one other classifier commonly used for the classification of coronary artery diseases. Gola et al. (2020) compared machine learning methods and different methods in their study to classify coronary artery disease. In their findings, they determined the AUC value of the Naive Bayes classifier as 0.819 [27]. Setiawan et al. (2014) compared the performances of Naive Bayes and J48 classifiers with different dimension reduction methods to increase the classification performance of coronary artery disease in their study [28]. Arjenaki et al. (2015) used the Naive Bayes method and SVM classifiers for the diagnosis of coronary artery diseases. The Naive Bayes classifier provided an accuracy rate of approximately 85% [29]. Random Forest is one of the classifiers that can provide high accuracy performance in diagnosing diseases. Researchers have used the random forest classifier to classify many diseases. Ani et al. (2016) obtained the accuracy performance of the random forest classifier as 89% to predict the risk factors of coronary artery diseases [30]. The random forest classifier have generally provided high accuracy performance in the classification of heart diseases [31-32].

In our study, the classification performances of Random Forest, SMO, Naive Bayes classifiers and Stacking ensemble learning methods were compared for the classification of coronary artery diseases. In our model, the Naive Bayes classifier has an accuracy performance of 0.774. The accuracy performance of the SMO classifier was obtained as 0.883. Finally, the accuracy performance of the Random Forest classifier was obtained as 0.908. The performances of the classifiers in our model are compatible with the findings of the studies in the literature. Stacking ensemble learning method has higher accuracy performance than classifiers. The accuracy value of the stacking ensemble learning method was obtained as 0.933. In our study, the stacking ensemble learning method achieved higher accuracy than the classifiers in the model for the classification of coronary artery diseases. Lo et al. (2016) compared the classification performances of 7 classifiers and ensemble learning methods for the diagnosis of coronary artery diseases in their study. They stated that the ensemble method provided the highest performance [33]. The findings we obtained in our study are consistent with the findings of the literature.

Ensemble learning methods can provide a successful classification for the classification of diseases. Ensemble learning methods can generally provide higher classification performance against single classifiers. The choice of meta classifier in the stacking ensemble learning method significantly affects the classification performance. Choosing the appropriate meta classifier for the model can improve the performance. The compliance of the classifiers included in the ensemble learning model can affect the classification performance. Increasing the number of samples included in the model can contribute to the increase in classification performance.

5. CONCLUSION

In this study, the performances of machine learning methods and ensemble learning method in the classification of coronary artery disease were compared. It was determined that the predictor variables that make the most essential contribution to the classification of coronary artery diseases are BUN, MPV, Age, AST and Monocyte, respectively. In the model, the classification performances of the SMO, Naive Bayes, Random forest classifiers and the Stacking ensemble learning method were compared. In the stacking ensemble learning method, the ensemble model consists of SMO, Naive Bayes and Random Forest classifiers. The meta classifier of the ensemble method is determined as "Logistic". Naive Bayes, SMO and Random forest classifiers achieved an accuracy performance of 0.774, 0.883 and 0.908, respectively. Stacking ensemble learning method successfully classified the diseases with an accuracy of 0.933. Stacking ensemble learning method classified coronary artery diseases with higher accuracy than the other classifiers. The stacking ensemble learning method can be successfully applied for the classification and diagnosis of coronary diseases.

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