Intelligent Automation & Soft Computing
DOI:10.32604/iasc.2021.018382
Article

Tech Science Press

Predicting Heart Disease Based on Influential Features with Machine Learning

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Received: 06 March 2021; Accepted: 11 May 2021

Abstract: Heart disease is a major health concern worldwide. The chances of recovery are bright if it is detected at an early stage. The present report discusses a comparative approach to the classification of heart disease data using machine learning (ML) algorithms and linear regression and classification methods, including logistic regression (LR), decision tree (DT), random forest (RF), support vector machine (SVM), SVM with grid search (SVMG), k-nearest neighbor (KNN), and naive Bayes (NB). The ANOVA F-test feature selection (AFS) method was used to select influential features. For experimentation, two standard benchmark datasets of heart diseases, Cleveland and Statlog, were obtained from the UCI Machine Learning Repository. The performance of the machine learning models was examined for accuracy, precision, recall, F-score, and Matthews correlation coefficient (MCC), along with error rates. The results indicated that RF and SVM with grid search algorithms performed better on the Cleveland dataset, while the LR and NB classifiers performed better on the Statlog dataset. Outcomes improved significantly when classification was performed after applying AFS, except for NB, for both datasets.

Keywords: LR; DT; RF; KNN; SVM

1 Introduction

Heart disease is a one of the onerous health issues, and several people worldwide are suffering from this disease [1]. According to the World Health Organization (WHO), heart or cardiovascular diseases are responsible for the highest number of deaths worldwide of any disease. Current trends indicate that India will soon rank first in the number of heart disease cases [2]. According to the National Center for Biotechnology Information (NCBI), 23.2 million deaths occurred due to heart disease in the United States (US) in 1990, increasing to 37 million in 2010, an increase of 59% [3]. Heart disease is the preeminent cause of death among those over 30 years of age in Africa [4]. More than 3.8 million deaths in Europe and 1.7 million deaths in the European Union occurred because of heart disease [5]. Large volumes of heart disease data are collected from hospitals globally and can be used to manually estimate disease rates. Nonetheless, the data so far regarding the risk of diseases and their symptoms have not been efficiently translated [6]. Heart disease is commonly accompanied by breathlessness, weakness in the body, and swollen feet [7]. Researchers have attempted to develop techniques for its early detection.

Early diagnoses continue to be less effective due to lower accuracy and longer execution time [8]. A diagnosis of heart disease is made by analysis of a patient's medical history, physical examination, and related symptoms, and the results are not accurate. A computational analysis is accurate but expensive [9]. Deaths due to heart disease are directly proportional to age, signifying that its probability of occurrence increases with age [10]. Several researchers have used the Cleveland and Statlog datasets of the UCI Machine Learning (ML) Repository to detect heart disease [11−12]. The accuracy of ML algorithms can be enhanced through proper balancing of training and testing datasets. Feature selection reduces dimensionality and increases the efficiency and accuracy of classification [13]. Li et al. [14] proposed feature selection methods for different sample sizes. Cai et al. [15] discussed evaluation measures of feature selection to improve the performance of ML algorithms, and highlighted the future challenges of feature selection. Li et al. [16] highlighted the feature selection challenges in big data and discussed its importance in enhancing learning performance.

Various data mining and ML algorithms have been suggested for the early detection of heart disease. Khateeb et al. [17] applied k-nearest neighbor (KNN) classification to predict heart disease with 80% accuracy. Olaniyi et al. [18] proposed a three-phase method based on an artificial neural network (ANN) for heart disease detection in angina, with accuracy of 88.89%. Jabbar et al. [19] developed an ML-based diagnosis system using ANN with feature selection algorithms, and reported good accuracy. Selvakumar et al. [20] developed a structure risk minimum support-based vector machine to predict heart disease that performed better than support vector machine (SVM). Palanappan et al. [21] suggested an expert medical diagnosis system to detect heart disease, using ML prediction models including naïve Bayes (NB), decision tree (DT), and ANN. The highest accuracy, 88.12%, was achieved by ANN. El et al. [22] compared the performance of the Bayesian network, NB, SVM, neural network, C4.5, and DT classifiers as applied to a heart disease dataset, and found NB to perform best. Samuel et al. [23] applied ANN with the fuzzy approach in a medical decision support system for heart disease prediction, and reported 91% accuracy. Liu et al. [24] used relief and rough set techniques to classify heart disease with 92% accuracy. Bharati et al. [25] concluded that different data-mining techniques, such as classification, clustering, association rules, and hybrid algorithms, led to better performance and higher accuracy rates. Haq et al. [26] used a sequential backward selection algorithm for feature selection, and KNN for classification to predict heart disease, with good performance in terms of accuracy. Several researchers have used feature selection algorithms along with classifiers. Wijaya et al. [27] improved the performance of the NB, DT, and KNN classifiers to detect heart disease by applying particle swarm optimization (PSO) for feature selection, using experimental data from the UCI repository. Similarly, Feshki et al. [28] applied PSO with neural network feedforward backpropagation to the diagnosis of heart disease, using the Cleveland Heart Disease Dataset from the UCI ML Repository for validation, and considering 14 of its attributes. An accuracy of 91.94% was achieved. Jabbar et al. [29] used NB classification, with a genetic optimization algorithm to remove redundant features, to predict heart disease. This method achieved the highest accuracy compared to all other methods. Ali et al. [30] refined the features and resolved the problems of overfitting and underfitting with the model, using deep neural networks to eliminate irrelevant features. The accuracy was 93.33%. Yang et al. [31] proposed a prediction model for heart disease using an optimized fuzzy inference system based on an adaptive network with linear discriminant analysis. Yekkala et al. [32] analyzed methods, such as bagged tree, AdaBoost, and random forest (RF) with PSO to predict the occurrence of heart disease, with bagged tree and PSO achieving the highest accuracy. Paul et al. [33] used a genetic algorithm to diagnose heart disease, with the assistance of a fuzzy decision support system, with 80% accuracy. Dubey et al. [34,35] suggested different variations of clustering algorithms for disease detection.

The present research work proposes an ML-based method to predict heart disease. Linear regression and classification methods, such as logistic regression (LR), DT, RF, SVM, SVM with grid search (SVMG),

KNN, and NB, are used, and ANOVA F-test feature selection (AFS) is applied for feature selection. The major objectives of this research are:

- the study and analysis of the effect of various ML algorithms in the classification of heart diseases;
- to analyze and predict the effects of attributes and their correlation on heart disease datasets;
- to analyze the combined performance of ML algorithms and feature selection (FS).

We achieved these objectives by studying the implications of ML models and prediction strategies, based on the model design and implementation with the feature disease classification.

2 Materials and Methods

Experiments were performed on two standard benchmark heart disease datasets, Cleveland (303 instances) and Statlog (270 instances), from the UCI ML Repository [36]. Some 14 of their 76 attributes are used in most published studies [37]. These are age, sex, chest pain (cp), resting blood pressure (trestbps), cholesterol (chol), fasting blood sugar (fbs), resting electrocardiogram (restecg), maximum heart rate achieved (thalach), exercise-induced angina (exang), ST depression induced by exercise relative to rest (oldpeak), slope of peak exercise ST segment (slope), number of major vessels (ca), thalassemia (thal), and predicted value (target). Target values of 0 and 1 respectively indicate the non-appearance and appearance of heart disease. For accurate prediction and analysis, the following classification methods were applied to the datasets. Regression was used to determine the correlation between attributes, and the AFS method [38] to select influential features.

2.1 Linear and Nonlinear Regression

Linear regression describes the relation between the target and predictors using a straight line. LR is a supervised learning method of classification used to predict target variables [39,40].

2.2 Decision Tree

DT can resolve regression and classification problems using a tree representation. Each leaf node in a tree represents a class label, and internal nodes represent attributes [41].

2.3 Random Forest

In RF, multiple decision trees are created during training, and the final prediction is based on the predictions obtained from all of them [42].

2.4 K-Nearest Neighbor

KNN is an ML algorithm that be used for both classification and regression [43]. Its performance relies mainly on the value of k and the distance between neighbors.

2.5 Support Vector Machine

SVM is a supervised learning method that can be used for classification and regression [44]. An optimal combination of parameters will enhance its performance. This can be achieved by a grid search, which also helps to avoid overfitting [45].

2.6 Naive Bayes

NB classification utilizes the concept of Bayes' theorem of probability, which is based on the concept of conditional probability, such as an event (E) will happen given that another event (E') has already happened [46]. Fig. 1 shows a flow diagram of our approach.

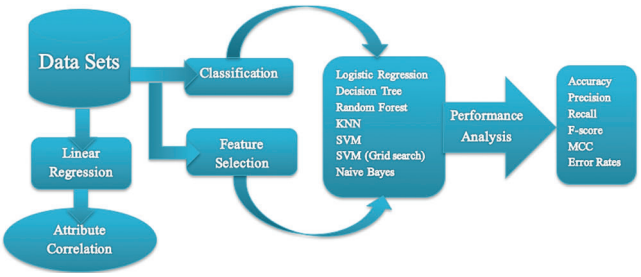


Figure 1: Flowchart of the proposed work

3 Experimental Results and Analysis

Classification algorithms were evaluated on the heart disease datasets mentioned above. Experiments were performed on an Intel Pentium G3220T CPU at 2.20 GHz, with a 32-bit Windows 7 operating system. Python and tkinter were used for analysis and graphical representation. We present the experimental results from the application of linear regression and classification methods such as LR, DT, RF, KNN, SVM, SVMG, and NB, along with AFS, on the heart disease datasets.

3.1 Result Based on Linear Regression

The heat maps in Fig. 2 show the correlations between the features of datasets. A heat map is a two-dimensional representation of data using colors to indicate values, which helps in visualizing the data. Linear regression uses coefficients to define the relationship between independent and dependent variables. Fig. 3 presents the coefficient of each attribute corresponding to the target attribute of both datasets. Coefficients of attributes can be either positive or negative, where a positive coefficient indicates a proportional relationship, and a negative value indicates inverse proportionality. Hence the target value increased with cp in both datasets, and it decreased with the increase in fbs in the Statlog dataset. The performance of the linear regression model was evaluated based on the coefficient of determination (R^2), mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE).

The coefficient of determination represents how strong the values fit compared to the original values. Its value ranges from 0 to 1; the higher the better. MAE is the variation between the original and forecast values, obtained by averaging the absolute difference over the dataset. RMSE is the square root of the mean squared error.

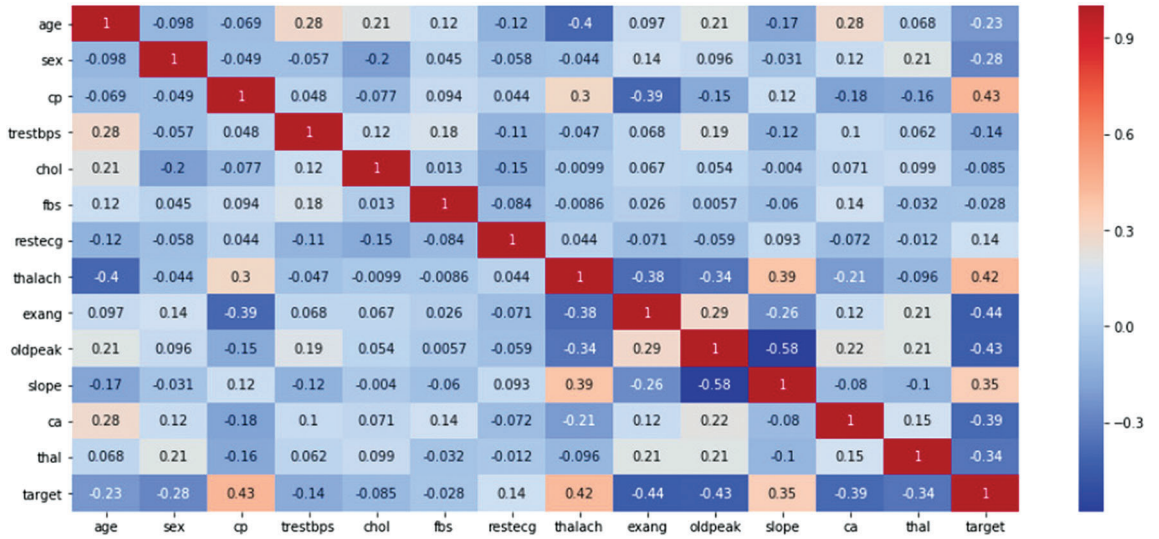
Tab. 1 presents the testing parameters of linear regression based on both datasets, where the test data was considered from 15% to 40%. The highest coefficient of determination of 56% for the Cleveland dataset and 60% for the Statlog dataset was obtained for 40% of the test data, whereas the minimum error was observed for 20% of the test data.

3.2 Result Based on Classification Methods Without AFS

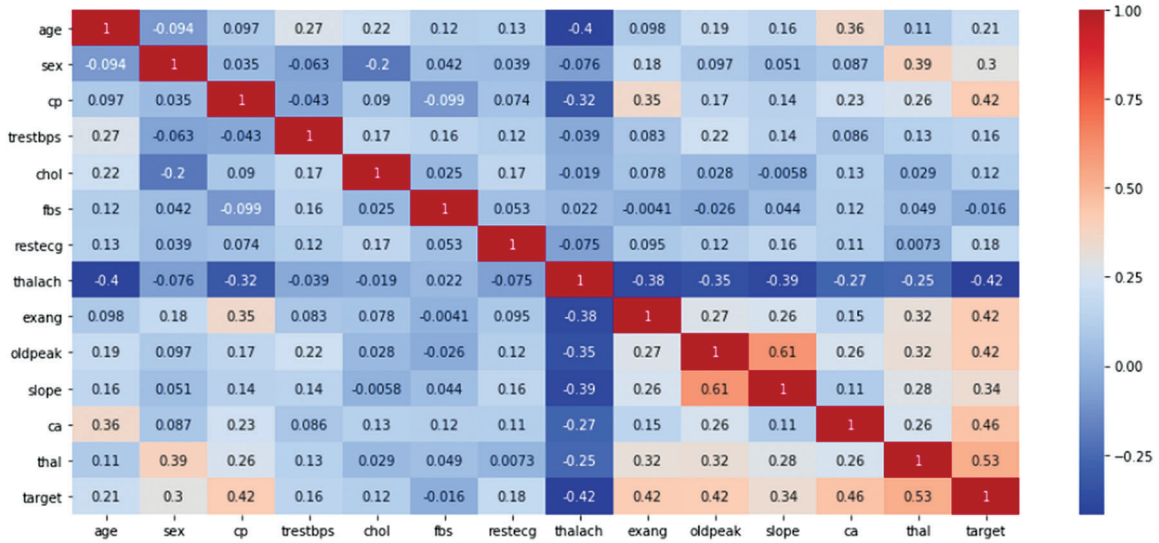
We evaluated the performance of the classification model by accuracy, precision, recall, F-Score, and Matthews correlation coefficient (MCC), as described in Tab. 2. TP indicates true positive, TN is true negative, FP is false positive, and FN is false negative.

Tabs. 3 and 4 present the accuracy, precision, recall, F-score, MCC values, and error rates (MAE and RMSE). Precision, recall, and F-score values are either 0 or 1, with 0 representing the non-appearance of heart disease and 1 representing its appearance. Here, the test data were considered from 15% to 40%. LR performed well on both datasets. In terms of classification reports and error rates, LR performed better when the test data were closer to 20%. Similar to LR, DT performed better with the 20% test data in terms of both classification and error rates. RF performed better than DT in all aspects for both

datasets. Using this method, the highest accuracies of 87% for the Cleveland dataset and 89% for the Statlog dataset were obtained with 20% test data. The classifier performed better with the 20% test data on both datasets. SVM performed well, with the highest accuracy value, 87% (with 20% testing data), for both datasets. Tab. 4 shows that the performance of SVM may be improved by adding grid search. NB performed well with 20% test data, achieving 87% accuracy and 74% MMC for the Cleveland dataset, and 91% accuracy, and 81% MMC for Statlog. Because the value of k in KNN plays an important role, different values were selected based on their error rates, as presented in Figs. 4 and 5. The minimum error containing the K value corresponding to the test data percentage was used for classification in both datasets to achieve the maximum accuracy. As seen in Figs. 4 and 5, the minimum error rates containing k values were 16, 11, 10, and 19 for 15%, 20%, 30%, and 40% testing data, respectively, for the Cleveland dataset, with corresponding values of 19, 19, 17, and 3 for the Statlog dataset.



(a)



(b)

Figure 2: Representation of correlation features of cleveland and statlog dataset through heat map. (a) Cleveland. (b) Statlog

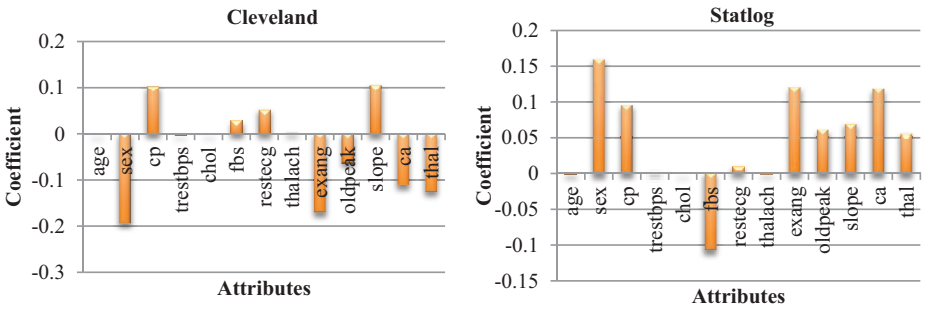


Figure 3: Coefficient of each attributes of heart diseases datasets

Table 1: Testing parameters of datasets based on linear regression

Test data		15%	20%	30%	40%
Cleveland dataset	Coefficient of determination	0.52	0.50	0.54	0.56
	MAE	0.29	0.26	0.30	0.30
	MSE	0.13	0.11	0.15	0.15
	RMSE	0.37	0.34	0.38	0.39
Statlog dataset	Coefficient of determination	0.54	0.53	0.55	0.60
	MAE	0.28	0.27	0.29	0.30
	MSE	0.11	0.10	0.13	0.15
	RMSE	0.34	0.32	0.36	0.39

Table 2: Performance parameters of classification method

Parameter	Description
Accuracy	$\frac{TP + TN}{TP + FP + FN + TN}$
Precision	$\frac{TP}{TP + FP}$
Recall	$\frac{TP}{TP + FN}$
F-Score	$\frac{2 \times (recall \times precision)}{recall + precision}$
MCC	$\frac{(TP \times TN - FP \times FN)}{\sqrt{((TP + FP) \times (TP + FN) \times (TN + FP) \times (TN + FN))}}$

Fig. 6 compares the classification algorithms on accuracy. The highest accuracy was achieved by SVM with grid search, and was 89% (with 20% testing data) for the Cleveland dataset. LR and NB had 91% accuracy for the Statlog dataset. Fig. 6 shows that suitable accuracy was achieved by all algorithms except KNN on both datasets with 20% test data. Only KNN demonstrated superior accuracy with the test data of 15% for the Cleveland dataset.

Table 3: Performance analysis based on LR, DT, RF, and SVM for both datasets

Methods			LR				DT				RF				SVM			
Test data(%)			15	20	30	40	15	20	30	40	15	20	30	40	15	20	30	40
CLEVELAND	Accuracy(%)		15	20	30	40	15	20	30	40	15	20	30	40	85	87	82	85
	Precision(%)	0	85	87	82	84	77	82	76	81	85	87	84	85	79	86	80	81
		1	79	86	80	81	65	76	70	78	82	89	84	81	89	88	82	88
	Recall(%)	0	89	88	82	86	87	89	82	82	86	85	83	88	83	86	78	85
		1	83	86	78	81	83	90	80	75	78	83	78	85	86	88	84	86
	F-Score(%)	0	86	88	84	86	71	75	72	84	89	91	88	86	81	86	79	83
		1	81	86	79	81	73	83	75	76	80	86	81	83	87	88	83	87
	MCC(%)		87	88	83	86	78	81	77	83	88	88	85	87	69	74	62	70
	Error rate(%)	MAE	69	74	63	67	54	65	52	60	64	71	62	62	15	13	18	14
		RMSE	15	13	18	16	23	18	24	19	15	13	16	14	39	36	43	38
STATLOG	Accuracy(%)		35	36	43	40	48	42	49	44	39	36	40	38	86	87	83	77
	Precision(%)	0	88	91	88	84	78	83	72	67	86	89	83	81	84	88	82	76
		1	85	89	85	81	75	82	80	70	81	86	80	78	88	85	85	78
	Recall(%)	0	93	94	92	91	85	88	62	62	93	94	91	88	91	91	92	87
		1	96	97	96	95	91	94	71	76	96	97	96	94	78	81	69	62
	F-Score(%)	0	78	81	75	69	61	67	72	53	72	76	62	62	87	90	87	81
		1	90	93	90	88	82	87	75	73	88	91	87	85	82	83	76	69
	MCC(%)		85	87	83	78	71	76	67	57	81	84	74	73	70	73	64	52
	Error rate (%)	MAE	76	81	74	68	56	65	43	30	61	61	61	50	14	12	17	23
		RMSE	12	09	12	15	21	17	28	33	14	11	17	19	38	36	41	48

Table 4: Performance analysis based on SVMG, KNN and NB for both datasets

Methods			SVMG				KNN				NB			
Test data (%)			15	20	30	40	15	20	30	40	15	20	30	40
CLEVELAND	Accuracy (%)		85	89	82	86	81	76	70	73	81	87	84	84
	Precision (%)	0	79	89	80	81	68	77	65	68	71	84	78	79
		1	89	88	82	88	95	74	73	77	88	90	89	88
	Recall (%)	0	83	86	78	85	94	69	68	69	83	90	88	85
		1	86	91	84	86	71	81	70	76	79	84	80	83
	F-Score (%)	0	81	88	79	83	79	73	67	69	77	87	83	81
		1	87	89	83	87	82	78	71	76	83	87	84	85
	MCC (%)		69	77	62	70	65	51	40	45	61	74	68	67
	Error rate (%)	MAE	15	11	18	14	19	24	30	27	19	13	16	16
		RMSE	39	33	43	38	44	49	55	52	44	36	40	40

(Continued)

Table 4 (continued).

	Methods		SVMG				KNN				NB			
STATLOG	Accuracy (%)		86	89	83	83	73	76	70	69	88	91	84	81
	Precision (%)	0	81	85	82	81	75	81	76	72	85	89	82	79
		1	93	100	85	89	71	68	62	63	93	94	88	83
	Recall (%)	0	96	100	92	94	78	79	76	75	96	97	94	90
		1	72	71	69	69	67	71	62	60	78	81	69	67
	F-Score (%)	0	88	92	87	87	77	80	76	73	90	93	88	84
		1	81	83	76	78	69	70	62	61	85	87	77	74
	MCC		71	78	64	66	46	50	38	35	76	81	66	60
	Error rate	MAE	14	11	17	16	26	24	29	31	12	09	16	19
		RMSE	38	33	41	40	51	49	54	56	34	30	40	44

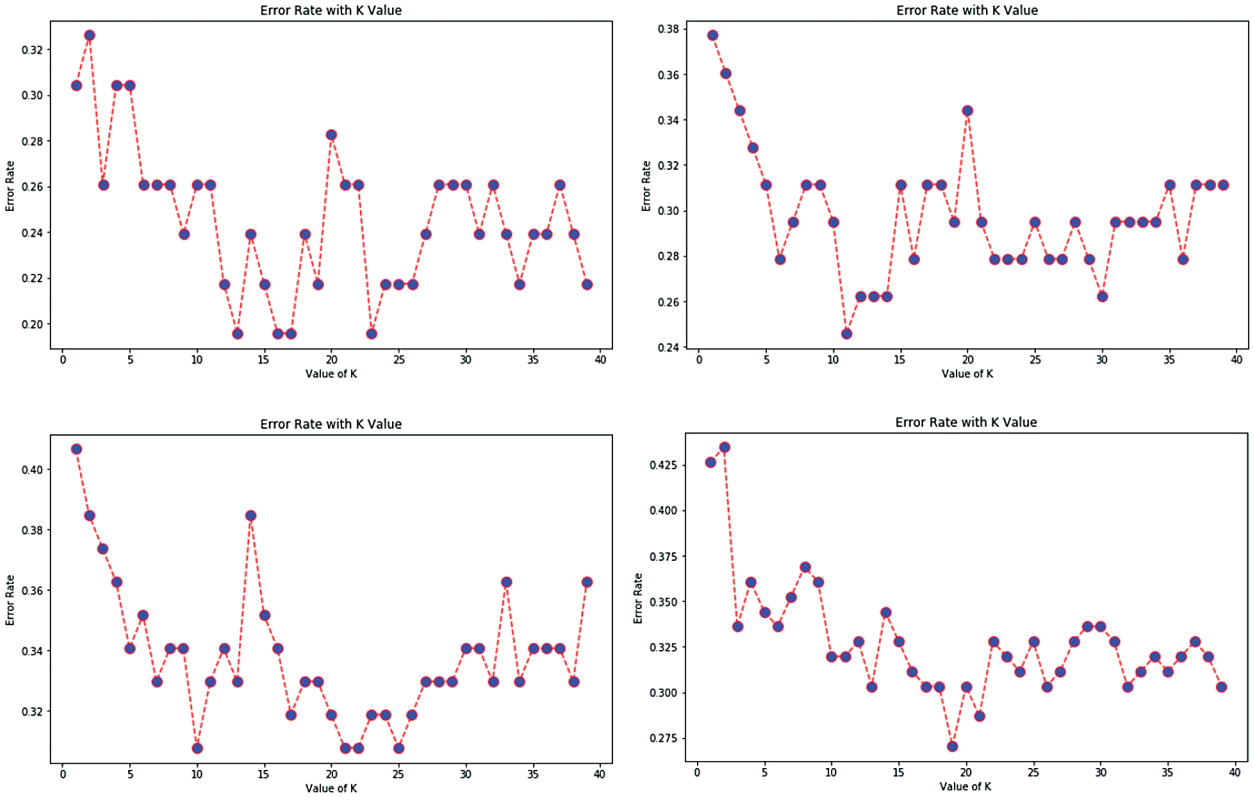


Figure 4: Error rates with value of K in cleveland dataset in case of KNN

Fig. 7 compares the classification algorithms in terms of precision. The highest precision was the 89% achieved by SVM with grid search (with 20% testing data) for the Cleveland data. SVM with grid search, LR, and NB achieved the highest precision of 91% for the Statlog dataset. Fig. 8 compares the classification algorithms in terms of recall. SVM with grid search achieved the highest recall, 89% (with 20% testing data), for the Cleveland data. LR and NB achieved the highest recall of 91% for the Statlog dataset.

Fig. 9 compares the classification algorithms in terms of error rates. SVM with grid search achieved the minimum error rate, 0.11 (with 20% testing data), for the Cleveland dataset, and the minimum error rate of 0.09 was achieved by LR and NB on the Statlog dataset. All classification algorithms except KNN performed well with 20% testing data on the Cleveland dataset.

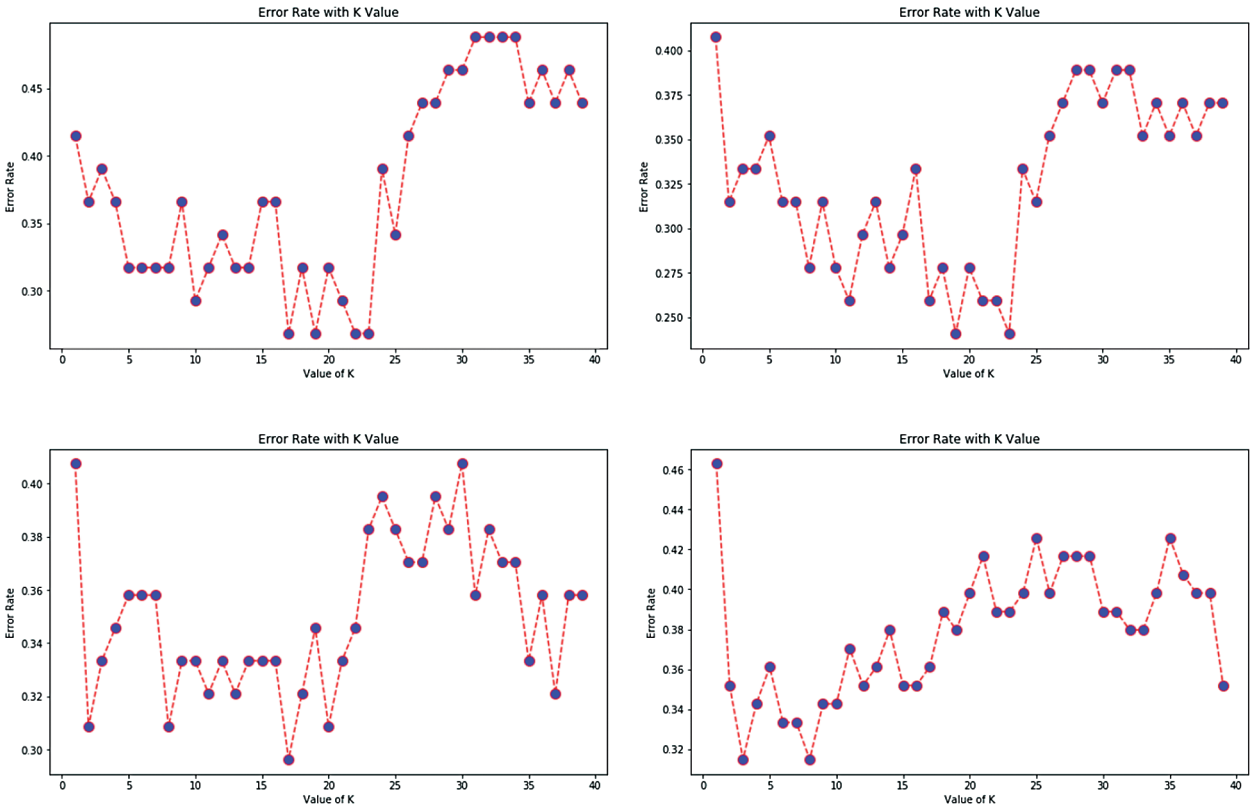


Figure 5: Error rates with value of K in statlog dataset in case of KNN

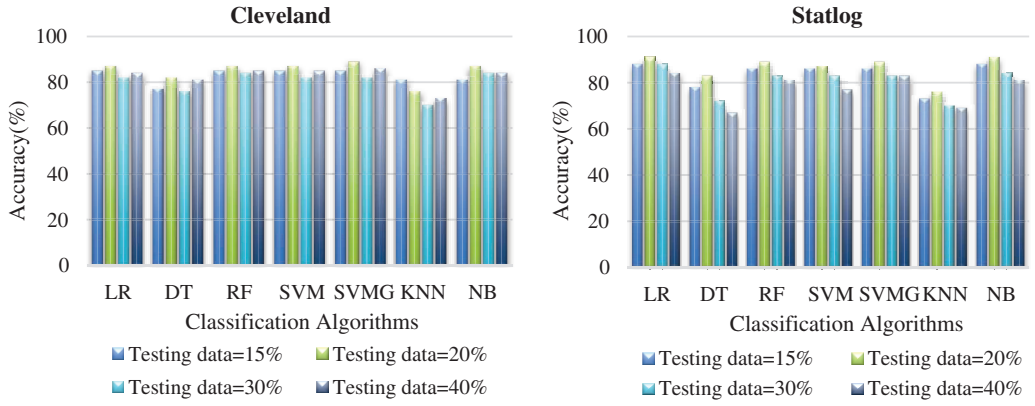


Figure 6: Comparison of classification algorithms with their accuracy for both datasets

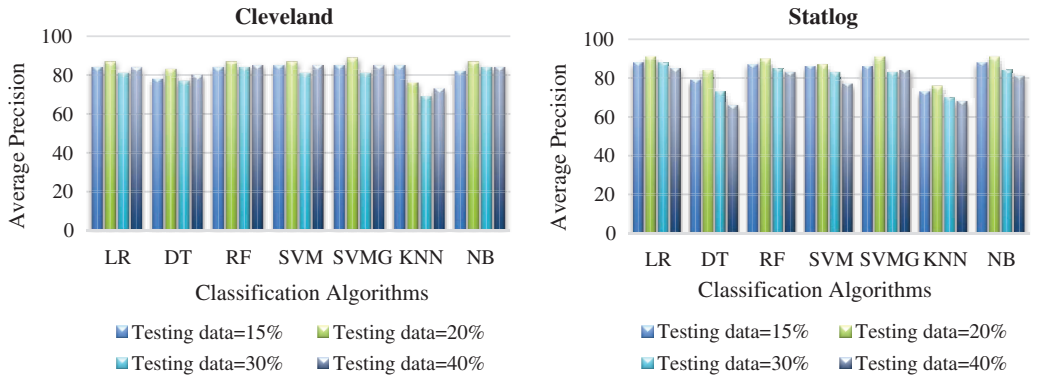


Figure 7: Comparison of classification algorithms with their average precision for both datasets

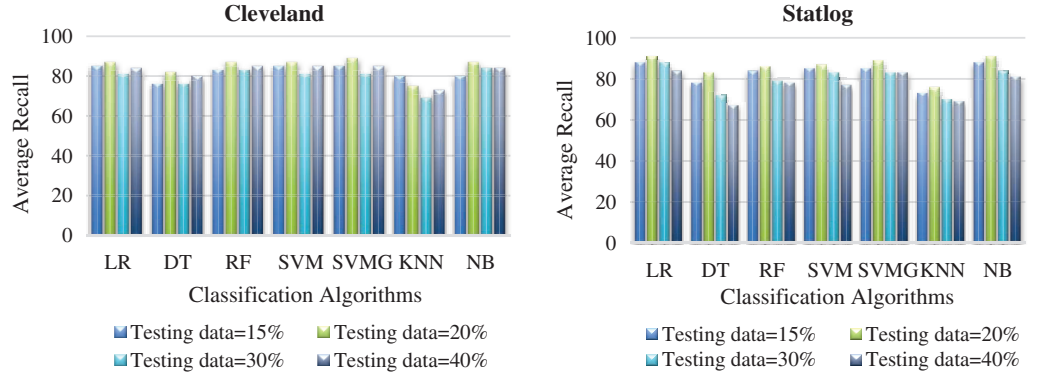


Figure 8: Comparison of classification algorithms with their average recall for both datasets

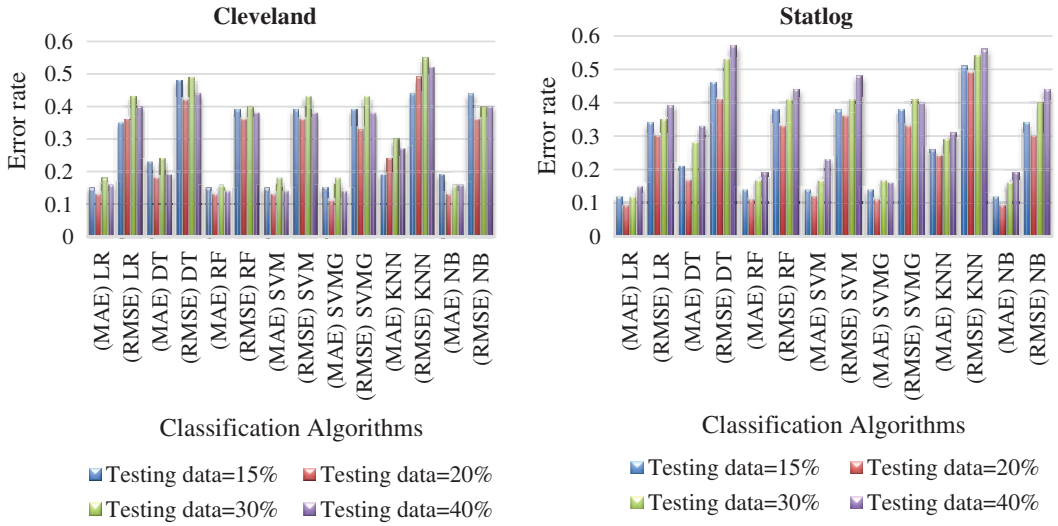


Figure 9: Comparison of algorithms with their error rate for both datasets

3.3 Results Based on the Classification Methods With AFS

Fig. 10 presents the score of each feature calculated using the AFS method for both datasets. The top seven features were cp, restecg, thalach, exang, oldpeak, slope, ca, and thal, which were selected to predict heart diseases. High-scoring features were more effective than low-scoring features.

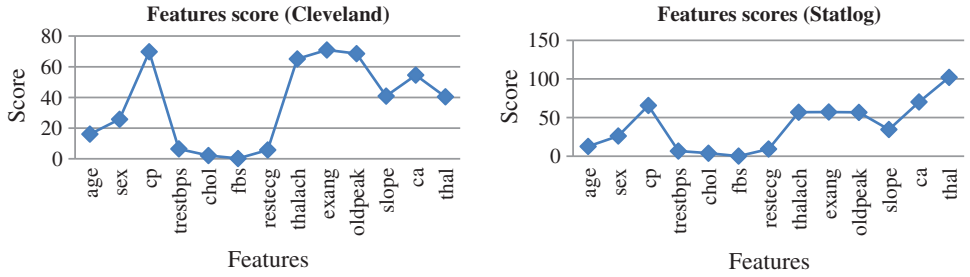


Figure 10: Feature scores for both dataset by using AFS method

Tab. 5 presents the accuracy, precision, recall, F-score, MCC values, and error rates (MAE and RMSE) for the top seven selected features on both datasets. With 89% accuracy, LR and SVM performed better than DT, RF, KNN, and NB on the Cleveland dataset with the selected features. For the Statlog dataset, LR performed better, with an accuracy of 93% with the selected features. Here, 20% of the data was considered as the test data. Different K values were selected based on their error rates, as shown in Fig. 11, and the minimum error containing k value was used for classification in both datasets to achieve the maximum accuracy. We used k = 18 for the Cleveland dataset and k = 3 for the Statlog dataset.

Table 5: Performance analysis based on classification methods with FS

Classification Methods			LR	DT	RF	KNN	SVM	NB
Cleveland dataset	Accuracy (%)		89	84	88	82	89	86
	Precision (%)	0	89	81	86	82	89	83
		1	88	87	89	82	88	87
	Recall (%)	0	86	86	86	79	86	86
		1	91	81	89	84	91	84
	F-Score (%)	0	88	83	86	81	88	85
		1	89	84	89	83	89	86
	MCC (%)		77	68	74	64	77	71
Statlog dataset	Accuracy (%)		93	84	90	82	91	88
	Precision (%)	0	89	82	82	83	87	84
		1	100	87	100	79	100	94
	Recall (%)	0	100	91	100	88	100	97
		1	83	73	75	71	76	72
	F-Score (%)	0	94	86	92	85	93	90
		1	89	80	85	75	86	81
	MCC (%)		85	66	74	61	81	73

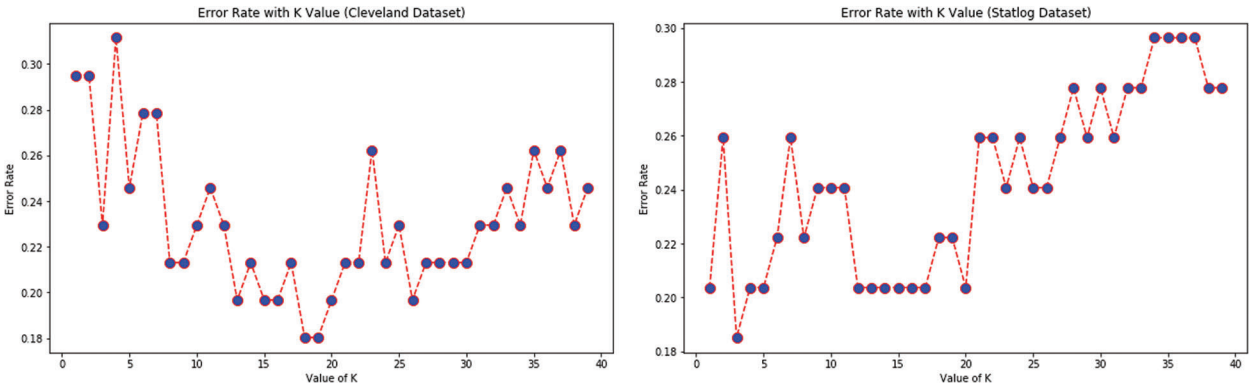


Figure 11: Error rate with K value for KNN with FS for both datasets

Tab. 6 compares classification results, including accuracy, MCC, average precision, recall, and F-score, without and with FS. Classification algorithms with FS performed better than those without FS on all parameters except NB.

Table 6: Comparison of performance between classification with FS and without FS

Classification Methods		LR	LR + FS	DT	DT+ FS	RF	RF + FS	KNN	KNN+ FS	SVM	SVM + FS	NB	NB + FS
Cleveland dataset	Accuracy (%)	87	89	82	84	87	88	76	82	87	89	87	86
	Precision (%)	87	89	83	84	87	88	76	82	87	89	87	85
	Recall (%)	87	89	83	84	87	88	75	82	87	89	87	85
	F-Score (%)	87	89	82	84	87	88	76	82	87	89	87	85
	MCC (%)	74	77	65	68	71	74	51	64	74	77	74	71
Statlog dataset	Accuracy (%)	91	93	83	84	89	90	76	82	87	91	91	88
	Precision (%)	92	95	84	85	90	91	75	81	87	94	92	89
	Recall (%)	89	92	81	82	86	87	75	80	86	88	89	85
	F-Score (%)	90	92	82	83	88	89	75	80	87	90	90	86
	MCC (%)	81	85	65	66	61	74	50	61	73	81	81	73

4 Discussion

We investigated ML algorithms including LR, DT, RF, KNN, SVM, SVMG, and NB. The AFS method was applied to select influential features to increase classification accuracy. The major findings were as follows:

a) The highest coefficient of determination was obtained with 40% test data, and the minimum error was observed with 20% test data for both datasets, implying better goodness of fit with 40% test data.

b) SVM with grid search outperformed in terms of accuracy on the Cleveland dataset, and LR and NB performed better on the Statlog dataset. With 20% test data, better accuracy was obtained for all algorithms except KNN on both datasets, demonstrating superior accuracy with 15% test data on the Cleveland dataset.

c) SVM with grid search had better recall and precision on the Cleveland dataset, as LR and NB did on the Statlog dataset. Like accuracy, better recall and precision were obtained for all algorithms except KNN on both datasets with 20% test data, demonstrating the highest recall and precision with 15% test data in the Cleveland dataset.

d) Better error rates were shown by SVM with grid search for the Cleveland dataset, and LR and NB for the Statlog dataset. All these algorithms outperformed in terms of error rates (MAE and RMSE) on both datasets with the selection of test data at or close to 20%.

e) The classifiers performed well in terms of early prediction of heart diseases based on previous data. Based on the parameters discussed in the above points, SVM with grid search performed better for the Cleveland dataset, whereas SVM with grid search, LR, and NB classifiers performed better for the Statlog dataset. Therefore, the overall performance of the classification algorithms was better with the selection of test data at or close to 20%.

f) In classification with AFS, the LR and SVM algorithms outperformed in terms of accuracy, precision, and recall on the Cleveland dataset, and LR performed better on the Statlog dataset.

g) Overall, classification algorithms with AFS performed better than those without it, for all parameters except NB.

h) ML classification approaches assisted in predicting heart diseases at an early stage using previous data, with an impactful selection of features leading to better predictive results.

This study had certain limitations. We did not consider attribute optimization, which can help to select a limited number of attributes that are impactful and may improve the classification, and we did not use a real dataset.

5 Conclusion

An efficient and accurate ML-based system to predict heart disease was developed. Linear regression and classification methods, such as LR, DT, RF, SVM, SVM with grid search, KNN, and NB, were used, and AFS was applied to select influential features. The proposed prediction system was tested on the Cleveland and Statlog datasets and evaluated based on the parameters of, accuracy, precision, recall, F-score, MCC, and error rates. We analyzed and compared classification without and with AFS, and found the latter better, with the exception of NB. The proposed approach of machine learning assisted in predicting heart diseases at an early stage using previous data and an impressive selection of features could lead to better prognosis results. This work can be replicated with more parameters and different other thresholding mechanisms in the direction of attribute utilization to detect different diseases.

Funding Statement: The authors received no specific funding for this study.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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