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Improvement of heart attack prediction by the feature selection methods

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Abstract: Prediction of a heart attack is very important since it is one of the leading causes of sudden death, especially in low-income countries. Although cardiologists use traditional clinical methods such as electrocardiography and blood tests for heart attack prediction, computer aided diagnosis systems that use machine learning methods are also in use for this task. In this study, we used machine learning and feature selection algorithms together. Our aim is to determine the best machine learning method and the best feature selection algorithm to predict heart attacks. For this purpose, many machine learning methods with optimum parameters and several feature selection methods were used and evaluated on the Statlog (Heart) dataset. According to the experimental results, the best machine learning algorithm is the support vector machine algorithm with the linear kernel, while the best feature selection algorithm is the reliefF method. This pair gave the highest accuracy value of 84.81%.

Key words: Heart attack prediction, machine learning algorithms, feature selection methods

1. Introduction

Damage to the heart muscle due to inadequate blood flow to a part of the heart is called a heart attack [1]. Early diagnosis, in which clinical methods such as electrocardiography (ECG) [2] and blood tests are usually used, is a vital step in reducing sudden deaths from heart attacks. ECG is the process of the recording the electrical activity of the heart over a period of time. With the help of ECG signals anomalies in the heart can be detected. In addition, blood tests are used to detect the proportion of some enzymes such as local CK-MB in the blood as an indicator for a possible attack. In recent years, troponin values have been also checked for the diagnosis of heart attacks [3].

Since the desire to achieve better results in health care services has increased the importance of computer-aided systems [4], they have begun to be used in addition to clinical methods. Therefore, data such as patient information, medical diagnostics, and medical images were started to be recorded [5]. Later, machine learning methods processing these data were used to build decision support systems. Some examples of these methods are as follows.

Tu et al. [6] used a bagging algorithm and J48 decision tree algorithm for heart attack prediction. According to their experiments, the bagging algorithm gave better results than the decision tree algorithm. Srinivas et al. [1] used classification algorithms such as rule-based decision tree, naïve Bayes, and artificial neural network to predict heart attacks. In addition, they used the one dependency augmented naïve Bayes classifier (ODANB) and naïve creedal classifier 2 (NCC2) for data preprocessing. In their study, variables of the prediction model were age, sex, blood sugar, and blood pressure. Deepika et al. used association rule mining

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for classifying heart attack types [7]. In this study, some attributes such as the number of the chest pain and age of the patient were used as patient characteristics. Jabbar et al. proposed a clustering and association rule mining algorithm to predict heart attacks [8]. Sudha et al. [9] proposed naïve Bayes, decision trees, and neural net classifiers for stroke crisis. Shouman et al. [10] proposed a k-means clustering algorithm with the decision tree for heart attack prediction. Vikas et al. [11] used three data mining techniques, namely classification and regression tree (CART), (iterative dichotomized 3) ID3, and decision table (DT). They revealed that the CART algorithm outperformed the other classifiers. Ganesh et al. [12] analyzed heart disease prediction approaches such as naïve Bayes, decision table, and J48. The best result was obtained with accuracy of 83.40% by using naïve Bayes.

Kora and Kalva [13] studied ECG signals for heart attack prediction. They used an improved bat algorithm to reduce the number of features of the ECG signals. Later, the selected features (20 best features from 200 features) were given as the input for the classifiers, i.e. SVM, KNN, Levenberg–Marquardt neural network (LM NN), and scalar conjugate gradient neural network (SCG NN). The best experimental result with accuracy of 98.90% was obtained by using LM NN. Soni et al. [14] used an algorithm named weighted association rule based classifier (WAC), based on association rule mining. They prepared a GUI and calculated the risk of a heart attack. Florence et al. [15] used decision trees and artificial neural networks to predict heart attacks. Moreover, they worked on a UCI dataset consisting of six features. Jabbar et al. [16] used a graph based association rules mining algorithm in the heart attack prediction problem. In a recent study, Krishnaiah et al. [17] conducted a review of the methods used to diagnose heart attacks and compared these methods. According to their study, fuzzy logic based intelligent techniques increased model accuracy.

In the present study, many machine learning methods and feature selection algorithms were used together to find the best match for heart attack prediction. Within the scope of our work, binary logistic regression (BLR), C4.5, C-RT, SVM with linear kernel (SVML), SVM with polynomial kernel (SVMP), SVM with RBF kernel (SVMR), SVM with sigmoid kernel (SVMS), ID3, k-nearest neighbor (k-NN), multilayer perceptron (MLP), multinomial logistic regression (MLR), and naïve Bayes (NB) were used. The machine learning algorithms used were compared based on accuracy, processing time, and receiver operating characteristic (ROC) values. The effects of the feature selection methods on the success of classification were also measured. The UCI Statlog (Heart) dataset was used in the experiments.

2. Methodology

Computer-aided methods such as machine learning algorithms are examined in this study. Association rule mining [7,8,14], fuzzy logic [17,18], genetic algorithms [19], clustering analysis [8,10], neural network algorithms [1,9,13,15,19,20], support vector machines [13], naïve Bayes [9,10,21], etc. have been used in this context so far.

Unlike previous studies, comparisons of many machine learning methods and feature selection algorithms were done. Twelve different classifiers and four different feature selection algorithms were used in this study.

2.1. Classification algorithms

Algorithms used in this study can be divided into four categories: regression analysis models, support vector machines, decision trees, and the others. Regression models explain the change in the target variable according to the changes in the predictor variables [22]. Although many regression models seem candidates to be tried, logistic regression models were used in this work. Logistic regression models are used for nonlinear data with categorical class variables [23]. The support vector machine (SVM) algorithm was first introduced by Vapnik et al. [24] and the aim of it is to group data according to the support vectors. It can be used for linear and nonlinear data but it is more suitable for the linearly separable ones. Therefore, nonlinear data map to the linear form by the help of kernel functions such as linear, polynomial, radial basis, and sigmoid kernels. These kernels are shown in Table 1.

Table 1. The SVM kernel types used in this study.

Kernel type	Kernel function
Linear kernel	$K(x,\ y){=}x^T y$
Polynomial kernel (degree of d)	$K(\boldsymbol{x},\boldsymbol{y}){=}\ (x^T y + c)^d$
Radial basis kernel (RBF)	$K(\boldsymbol{x},\boldsymbol{y}){=}\ e^{-\frac{\lVert \mathbf{x}-y \rVert^2}{2\sigma^2}}$
Sigmoid kernel	$K(\mathbf{x},\ \mathbf{y}) = \tanh(\alpha x^T y + c)$

Decision trees are easily understandable and interpretable classifiers [25]. These classifiers construct a tree from a set of the labelled training data using an information gain metric. Decision trees are often used in medical data analysis.

In addition to the others, k-NN, MLP, and naïve Bayes classifiers were examined for heart attack prediction in this study. The K-NN algorithm is performed according to similarity or distance [26]. Artificial neural networks (ANNs) are mathematical or computational models based on biological neural networks [20] and prediction is one of their abilities. As in previous studies, multilayer perceptron (MLP) was used for heart attack prediction. Another classifier is the naïve Bayes algorithm used in this study. This classifier has a structural model with a set of conditional probabilities [21]. The structural model is presented as a directed graph in which nodes present attributes and curves show the dependencies of attributes.

2.2. Feature selection

Feature selection is a method that improves classifier performance in machine learning systems by cancelling nondiscriminative features from the feature set. In this study, stepwise regression models, Fisher filtering (FF), and reliefF algorithms were used as feature selection methods.

Backward-logit (BL) and forward-logit (FL) are two main approaches in stepwise regression models [27]. The forward-logit model starts with zero variables and one variable is selected as a candidate each time. If the candidate variable positively affects the accuracy, it is added to the new feature set. This process continues until the end of the candidate variables in the main feature set. In the backward-logit model, the process starts with all variables in the main feature set, one variable is extracted from the feature set, and model accuracy is measured. If model accuracy worsens then variable extraction is cancelled; otherwise it is accepted. The other two methods for feature selection are FF [28] and reliefF [29] algorithm. Relief, which is an appropriate feature selection algorithm for binary classification, was proposed by Kira and Rendel [30]. Relief is a powerful method because it is not based on heuristics. Nevertheless, it cannot distinguish repeated features. Kononenko et al. adapted the algorithm to multiclass problems [31]. The filter approach consists of selecting the most appropriate variables for any subsequent machine learning algorithm used in the model. ReliefF and FF methods are both filter based and they are performed by selecting high-quality rank score.

3. Experimental study

In this study, the UCI Statlog (Heart) dataset (http://archive.ics.uci.edu/ml/datasets/Statlog+%28Heart%29) was used to evaluate the performance of each machine learning methods. There are 270 records in the data set and each record consists of 13 features extracted from the 76 features. The details of the dataset are shown in Table 2. In addition, we used 90% of the data for training and 10% for testing, and we employed 10-fold cross validation in all the experiments.

Table 2. The description of Heart disease dataset.

Feature name	Features
var1	age
var2	sex
var3	chest pain type (4 values)
var4	resting blood pressure
var5	serum cholesterol in mg/dL
var6	fasting blood sugar > 120 mg/dL
var7	resting electrocardiographic results (values 0, 1, 2)
var8	maximum heart rate achieved
var9	exercise induced angina
var10	old peak = ST depression induced by exercise relative to rest
var11	the slope of the peak exercise ST segment
var12	number of major vessels (0-3) coloured by fluoroscopy
var13	thal

3.1. Experimental design

In the experimental studies, classification algorithms such as logistic regression models, decision tree models, MLP, naïve Bayes, and SVM algorithms were used for heart attack prediction. These algorithms were evaluated in terms of accuracy, classification speed, and ROC analysis using the TANAGRA [32] machine learning tool. Optimization of the parameters whose details are shown in Table 3 is also performed. These parameter values were obtained with respect to the classification performance criteria such as model accuracy.

Furthermore, the contribution of feature selection in the experimental results was examined. Feature selection methods and the obtained feature sets are shown in Table 4.

Consequently, experiments were done based on the main feature set and subfeature sets.

3.2. Experimental results based on accuracy and time

At the beginning of the experiments, feature selection was not applied to the main feature set. According to this setting, used classifiers, their accuracy rates, the processing times, the correctly classified samples, and the incorrectly classified samples are presented in Table 5.

According to the overall accuracy rates and processing times, most of the classifiers gave high performance. Accuracy results of the eight classifiers are very close. Then the same experiments were repeated for the subset of the features to measure the contribution of feature selection. Every algorithm was applied to subfeature sets,

Table 3. The parameters of the machine learning algorithms.

Algorithms	The parameters and values	
C4.5	The minimum size of leaves	5
	Confidence level	0.25
C-RT	The minimum size of the node to split	10
	Pruning set size (%)	33
	The x-SE rule	1
SVM	The degree of kernel function	1
	Gamma	0
	Coefficient 0	0
	The complexity	1
ID3	The minimum size for split	200
	The minimum size of leaves	50
	Max depth of the tree	10
	Min-entropy gain for splitting	0.0300
K-NN	The neighborhood size (k)	5
	The distance method	Euclidian
MLP	The number of neurons	10
	Learning rate	0.1500
	The validation set proportion	0.20
	Max iteration	100
	Error rate threshold	0.01
Naïve Bayes	Lambda	0
Logistic regression models	The default parameters provided by TANAGRA	

Table 4. Feature selection algorithms and subfeatures.

Backward-logit selection	var3, var10, var12, var13
Forward-logit selection	var13, var12, var9, var10, var3
Fisher-filtering selection	var13, var12, var9, var8, var10, var3, var11, var2, var1
ReliefF selection	var2, var13, var7, var12, var3, var9

which were obtained by the feature selection algorithms. Experimental results of all combinations are given in Table 6.

The values in Tables 5 and 6 are summarized in Table 7.

At the end of the experiments, some valuable information was obtained in terms of model accuracy and processing time. According to the accuracy value, the highest classification success was obtained by the feature set extracted by the reliefF algorithm. Another notable outcome of the results indicated that none of the feature selection algorithms reduced the average processing time since the complexities of the most of the classifiers are not related to the number of features. While SVM-linear and naïve Bayes gave the highest accuracy, the lowest result was obtained with SVM-polynomial. The polynomial kernel was not suitable for this problem. The backward-logit based k-NN gave the lowest processing time value of 187 ms. The effect of feature selection on

Table 5. Model accuracy for the used classifiers without feature selection.

Model	TP	FN	FP	TN	Accuracy (%)	Time (ms)
BLR	130	20	27	93	82.59	359
C4.5	117	33	35	85	74.11	375
C-RT	117	33	40	80	72.96	375
SVML	130	20	27	93	82.59	375
SVMP	150	0	120	0	55.56	375
SVMR	127	23	29	91	80.74	375
SVMS	130	20	29	91	81.85	375
ID3	115	35	45	75	70.37	375
K-NN	111	39	52	68	66.30	547
MLP	127	23	29	91	80.74	1437
MLR	130	20	27	93	82.59	375
NB	130	20	27	93	82.59	359

Table 6. The accuracy of the classifiers when the method of feature selection varies.

	Backward logit	Forward logit	Fisher filtering	reliefF
Model	TP/FN/FP/TN	TP/FN/FP/TN	TP/FN/FP/TN	TP/FN/FP/TN
BLR	121/21/26/94	130/20/25/95	131/19/26/94	130/20/24/96
C4.5	131/19/30/90	129/21/30/90	126/24/37/83	135/15/31/89
C-RT	132/18/40/80	132/18/40/80	120/30/36/84	132/18/37/83
SVML	128/22/27/93	131/19/27/93	132/18/25/95	131/19/22/98
SVMP	150/0/120/0	150/0/120/0	150/0/120/0	150/0/120/0
SVMR	129/21/30/90	131/19/29/91	130/20/27/93	127/23/30/90
SVMS	130/20/35/85	135/15/31/89	132/18/25/95	134/16/26/94
ID3	115/35/45/75	115/35/45/75	115/35/45/75	115/35/45/75
K-NN	128/22/31/89	129/21/35/85	115/35/46/74	131/19/35/85
MLP	130/20/26/94	132/18/30/90	130/20/28/92	131/19/26/94
MLR	129/21/26/94	130/20/25/95	131/19/26/94	130/20/24/96
NB	130/20/26/94	132/18/26/94	133/17/24/96	132/18/26/94

the transaction time can be seen in Table 7. The highest processing time was achieved by the MLP algorithm without feature selection. Feature selection methods shortened the processing time of some classifiers such as K-NN and MLP.

3.3. Experimental results based on the ROC analysis

ROC is another common method used to evaluate the generalization performance of a classification algorithm. In the comparison model by using ROC analysis, area under curve (AUC) values are used. The AUC values obtained for classifiers are shown in Table 8.

As in the accuracy-based experiments, the performance of the algorithms and the effect of the feature selection were examined in the ROC analysis. Although 12 algorithms were tested in the correct recognition

Table 7. Model accuracy and the processing time for the models.

	Backward logit		Forward logit		Fisher filtering		reliefF		No feature selection	
Model	Acc (%)	Time	Acc (%)	Time	Acc (%)	Time	Acc (%)	Time	Acc (%)	Time
BLR	82.59	375	83.33	375	83.33	359	83.70	375	82.59	359
C4.5	81.85	359	81.11	391	77.41	407	82.96	375	74.81	375
C-RT	78.52	375	78.52	375	75.56	359	79.63	375	72.96	375
SVML	82.59	375	82.96	375	84.07	422	84.81	359	82.59	375
SVMP	55.56	390	55.56	375	55.56	391	55.56	359	55.56	375
SVMR	81.11	407	82.22	391	82.59	437	80.37	375	80.74	375
SVMS	79.63	438	82.96	390	84.07	438	84.44	359	81.85	375
ID3	70.37	359	70.37	360	70.37	360	70.37	375	70.37	375
K-NN	80.37	187	79.26	453	70.00	562	80.00	375	66.30	547
MLP	82.96	906	82.22	1015	82.22	1171	83.33	1109	83.70	1437
MLR	82.96	218	83.33	375	83.33	375	83.70	390	82.59	375
NB	82.96	203	83.70	375	84.81	360	83.70	359	82.59	359

Table 8. ROC AUC according to the feature selection methods.

Feature	NB	LR	MLP	K-NN	ID3	SVM	C-RT	C4.5
All	0.922	0.935	0.925	0.949	0.900	0.900	0.908	0.936
BL	0.881	0.901	0.894	0.945	0.900	0.900	0.880	0.922
FL	0.880	0.906	0.904	0.933	0.900	0.900	0.908	0.916
FF	0.917	0.921	0.904	0.951	0.900	0.900	0.908	0.916
relieff	0.897	0.909	0.907	0.934	0.900	0.900	0.908	0.878

experiments, 8 algorithms were tested in the ROC analysis due to the same results given by BLR and MLR. All SVM algorithms also gave the same ROC value. The AUC values are close to each other and the best performance was obtained by k-NN. In the ROC analysis experiments, there was a relation between the feature set sizes and the AUC values. The result obtained by the FF method was the only exception for this relation. Although the number of features was reduced, an increase in the AUC value was observed for the k-NN. It was also seen that SVM models gave the same results with a lower number of features and so it was not necessary to work with more features.

While overall accuracy is based on one specific cut point, ROC is based on all of the cut points. Therefore, accuracy and the ROC AUC values are different. The overall accuracy varies for different cut points.

3.4. Comparison of the other studies

There have been many studies about prediction of heart attacks. Some of them were fulfilled with models outside the classification. Our study uses classification algorithms and it works with the UCI Heart disease dataset. Therefore, our study was compared to similar studies in terms of the algorithms and the dataset (Table 9).

According to the comparisons between our study and the others, when taking all the feature selection algorithms into account, the most promising classifiers are SVM, naïve Bayes, and k-NN classifier for predicting heart attacks. In addition, the best feature selection algorithm was reliefF.

Table 9. Comparisons of the studies using UCI Heart Disease dataset.

Study	Algorithm and result
Tu et al. [3]	Bagging algorithm (81.41%)
	J48 decision tree (78.90%)
Srinivas et al. [4]	ODANB (80.46%)
	Naïve Bayes (84.14%)
Shouman et al. [8]	Decision tree (84.10%)
Vikas et al. [9]	CART (83.49%)
	ID3 (72.93%)
	Decision table (82.50%)
Hari Ganesh et al. [10]	Naïve Bayes (83.40%) Decision table (76.20%) J48 (77.50%)
Soni et al. [14]	WAC algorithm (81.51%)
Our study	SVM-linear (84.81%)
	SVM-sigmoid (84.44%)

4. Conclusions and future research

Clinical methods are usually used successfully in predicting heart attacks. In addition to these methods, computer aided systems also help doctors to predict heart attacks. In particular, machine learning methods enable us to predict the future and to unveil interesting patterns in the medical data.

In this study, twelve classifiers from different categories and four feature selection algorithms from two different categories were used for heart attack prediction. The models were compared according to the parameters such as model accuracy, processing time, and ROC analysis results. Experiments were conducted with and without feature selection to measure feature selection effect. Without feature selection, the best result, based on model accuracy, gave many classifiers. Eight classifiers gave accuracy of around 80%. BLR and naïve Bayes gave the best result in terms of processing time. The same algorithms also gave the best results according to model accuracy and processing time. Then the experiments were repeated by selecting features. With feature selection, even though not the case for all algorithms, some of them improved both processing time and model accuracy. The highest accuracy value was 82.59% without feature selection and it was improved to 84.81% with feature selection. SVM-linear and naïve Bayes gave model accuracy of 84.81%. Moreover, the best case for processing time was reduced from 359 ms to 187 ms. Among the four different feature selection methods, the best model accuracy is given by the reliefF algorithm according to the mean accuracy value. The most important example of the effect of the feature selection about model accuracy and processing time is the k-NN algorithm. With the help of the feature selection, the performance of the k-NN algorithm was increased while the processing time decreased. The feature selection for the k-NN algorithm also increased the ROC value. The best AUC value was obtained with k-NN when ROC analysis was performed on all algorithms. Although feature selection improved the results slightly in some algorithms, it gave significantly better performance in k-NN.

In this study, the feature selection algorithms increased the success rate in the SVM algorithm by 2.22% and increased the ROC value and correct recognition while decreasing the operation time in the k-NN algorithm. Therefore, when the right combinations are concerned, it was seen that feature selection in heart attack prediction studies has an improving role.

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