

APPLICATION OF COMPUTATIONAL INTELLIGENCE IN INTENSIFYING THE ACCURACY OF HEART DISEASE PROGNOSIS USING A MUTUAL VALIDATION

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ABSTRACT

Recently, the modern life style leads to the increase of the number of heart disease among human beings. One of the challenges in this realm is finding a way for fast and precise heart disease prognosis. In this paper, in order to increase the accuracy of the proposed models, we introduce a new classifying algorithm, which is used a 10-fold cross validation instead of dividing a data set in to two classes of test and train, and 10 times run each models. In the proposed algorithm, each models runs 100 times. This increases the reliability of models. In order to overcome the problem of over-training and under-training, database records are randomly displaced by randomize methods. Simulation results using UCI data sets show the performance of the proposed algorithm.

Keywords: Computational Intelligence; Heart Diseases; Classifying; Feature Selection; Mutual Validation

INTRODUCTION

Heart Disease

The heart is a pump or a pulsatile pump that consists of the four-hole structure including two atrias and two ventricles which lead the blood into whole body's organs. Therefore, the heart is a vital organ of the human body which constantly faced with several serious illnesses. Recent research on the heart disease show that, any condition in which the heart and blood vessels are damaged or not work properly would result in fatal and serious heart problems. Although heart disease symptoms vary among each individual, but in most cases there are no symptoms and the disease can only be detected when reach to advanced levels. Some common causes of heart disease include:

- 1- Discomfort in the chest: chest discomfort caused by narrowing of the arteries is called angina in chest. If the chest pain has no relation with physical activities, it is called non-angina pain.
- 2- Weakness and early fatigability: A common symptom in many cardiac and non-cardiac diseases such as endocrine and metabolic diseases is respiratory and mental problem. Heart failure (bradycardia), slow heart rate problems and valvular heart problem show early fatigability and weakness. Although symptoms such as shortness of breath, cough, slow pulse (heart rate less than 60 beats per minute), episodes of fainting, cold sweating, dizziness and heart problems can be helpful in diagnosis heart disease.
- 3- Shortness of breath: feel difficulty in breathing can have cardiac or non-cardiac causes.
- 4- Vertigo: Vertigo is one of the most common symptoms that can be caused by cardiac, neurological, metabolic or psychological problems. Lightheadedness, blurred vision and loss of balance, especially if accompanied by cold sweats can be caused by cardiac arrhythmia or low heart rate or low blood pressure.
- 5- Palpitations: feeling palpitations may be due to cardiac arrhythmia or anxiety resulting from the activities. If a person suffers sudden heart palpitations when resting and after a few minutes that palpitations discontinued, there is likely to be cardiac arrhythmia.
- 6- Sweating: Cold sweats are a common symptom of a heart attack, arrhythmia, bradycardia, and heart failure, which is often accompanied by other symptoms. If the cold sweats, accompanied by angina chest pain there is a possibility of heart attack.

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The main sections of this report are as follows:

Literature Review, Modeling, the software used for comparison, introduction to Databases, the 10-fold part, the pvc part, modeling on the set of selected variables, proposed model and conclusion.

Related Works

An Overview of the Heart Disease Prediction Works

Recently, several researchers have been used artificial intelligence techniques in order to predict heart disease. Most of researcher in data mining are specialist in one scientific field of studying such as medical, radiologist, sales manager, and businessman. They not only have access to data but also do efforts in gathering them. Their goal is to not only understand their data but also tend to discovered new knowledge related to the activity from data. Data holders' aim is to find new ways to solve problems (Shahrabi, 2009).

One of the general data sets for heart disease diagnosis is Cleveland data set from the California University in Ervin which is accessible for public usage. Many works have been done on finding effective medical diagnosis of different disease. Their aim is to have an effective disease prediction with less data features and they make it possible by using heart disease classifiers. (Awang *et al.*, 2008) and then (Asha *et al.*, 2010) distributed intelligent heart prediction system which is used a three levels architecture composed of decision tree, Naïve Bayes and neural network. Naïve Bayes with 96.6 % did a good prediction and need thirteen features for prediction. (Wasan *et al.*, 2006) reviewed several methods based on classification and data mining such as decision tree and applied artificial neural network rules for diabetic diagnosis.

Karllus *et al.*, (2006) introduced an effective search for heart disease diagnosis compared to the decision tree's rules. Anbarasi *et al.*, (2010) and Aha *et al.*, (1988) reviewed the each artificial intelligence algorithm effectiveness in heart disease prediction and two algorithms of NT growth and C4.5 decision trees gained 77% and 74.8% accuracy respectively. Detrano *et al.*, (1989) used probabilistic algorithms in artificial intelligence for risk prediction of the heart arteries Diseases. Results showed that patient with chest pain had a high risk of developing this type of heart disease Gennari *et al.*, (1989) presented a clustering system with 72.8% accuracy for patients clustering. Edmonds *et al.*, (2005) compared evolutionary computation approaches with the new approaches. This research applied on the Cleveland data sets.

Several researches also have been done for different aspects of heart disease prediction and applied on different data sets. Machine Learning (ML) algorithms which were used in these researches were included fuzzy; support vector clustering for heart disease identification; Prototype extended model using data mining techniques such as decision trees, Naïve Bayes and neural network; using hidden mark ov models, and features extraction for prediction improvement of the system (Nahar *et al.*, 2013)

Modeling

In this study, the following three criteria are used for providing a comparison among the well popular classification algorithms:

1. Accuracy: This indicator measures the accuracy of the forecast.
2. The True Positive (TP) rate: This indicator only considered accurate classification rate for the positive classes.
3. F-measure: It indicates the effectiveness of an algorithm when the accurate prediction rates for both of the classes are considered.
4. Time: This indicator considered training time to compare the computational complexity for learning algorithms.

In this paper 6 classification methods are used include Naïve Bayes, Support vector machine optimization (SMO), Support Vector Machine (SVM), k-nearest neighbor (IBK), decision tree boosting (AdaBoost), and decision tree J48. These classification algorithms were used in order to compare the effectiveness of FS.

Naïve Bayes is a simple classifying approach which is used a probabilistic knowledge. It is called Naïve because it relies on two main simple premises. First, predictive features are independent with respect to

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the subject class, and second, it is assumed that there are no secret or hidden features expected for the process (Rashedur, 2013). Support vector machine optimization (SMO) techniques for the first time described by (Cortes and Vapnik1995) and have been widely used in two classification problem. SVM changed linear data into discrete data in high dimension for separating and classifying data by quadratic (Hyunsoo, 2013). Support Vector Machine (SVM) is a supervised learning algorithms.SVM makes a hyperplane which divides samples in to two classes. It makes all the instance of a class on one side of the hyperplane, and the other classes in the other side of the hyperplane (Sumit, 2008).

A set of selected features tested by the well-known methods and with two different classifications as follows: probabilistic classification (Naïve Bayes) and the decision tree classification (C4.5). These algorithms have been selected because they represent different ways of learning and precise classification than the other algorithms (Rodríguez, 2007). C4.5 tree is another tree introduced by Quinlan for correcting the problems of the ID3 tree in 1993. The general principles of these two methods were similar (Korting 1997). This algorithm has been published under the license of Quinlan and he offered the other version named C5.0. This version lacks the proper implementation of the Matlab language, and except the original version of this program which is written in c++ and implemented by Quinlan, the only open source which is implementation in Weka is entitled J48. Rule-based methods (PART) are used to predict heart disease. In the next part the model is described in Weka software.

3-1 Software Used for Comparison

Many software programs for data mining and machine learning in different fields of data are available. Each of them according to the type of data being explored is focused on specific algorithms and makes a collection of updated machine learning algorithms and tools. Weka is pre-processed data software. This software is designed in a way that can be quickly tested current methods with so much flexibility on the new data sets. Weka which is extracted from the phrase “Waikato Environment for Knowledge Analysis”, was developed in New Zealand (Seyed, 2012).

3-2- Data Set

As mentioned in previous part, we used UCI data sets from the University of California (Uci, 2009; Uci, 2010). This data set contains 76 variable. Most of the above-mentioned research only used 14 variables for their models. These 14 variables are described in the following: (Yousefian, 2011)

1. Age: Age of the patient. (numeric);
2. Sex: male = 1, female = 0. (nominal);
3. Chest pain: common angina(angina), =1, uncommon angina (abnang)=2, non angina pain (notang)= 3, asymptomatic (asympt)= 4. (nominal);
4. Trestbps: patient’s resting blood pressure in mm Hg at the time of admission to the hospital (numeric);
5. Chol: Serum cholesterol in mg/dl;
6. Fbs: Boolean measure indicating whether fasting blood sugar is greater than 120 mg/dl: (1 = True; 0 = false) (nominal);
7. Restecg: electrocardiographic results during rest. Three types of values normal (norm), abnormal (abn): having ST-T wave abnormality, ventricular hypertrophy (hyp) (nominal);
8. Thalach: maximum heart rate attained (numeric);
9. Exang: Boolean measure indicating whether exercise induced angina has occurred: 1 = yes, 0 = no (nominal);
10. Oldpeak: ST depression brought about by exercise relative to rest (numeric);
11. Slope: the slope of the ST segment for peak exercise. Three types of values upsloping, flat, downsloping (nominal);
12. Ca: number of major vessels (0–3) colored by fluoroscopy (numeric);
13. Thal: the heart status (normal, fixed defect, reversible defect) (nominal);
14. The class attributes: value is either healthy or heart disease (sick type: 1, 2, 3, and 4).

Since in this research we used SMO classification algorithm which can only predict two categories problems. Thus, the five categories dataset which is used here, has changed to a five data set with two

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categories. These five categories represent a class of healthy subjects and four categories related to patients with different heart disease. In turn this new data set, has one positive class (healthy) and the rest consider as negative category (unhealthy).Table 1 shows the available data.

Table 1: The heart-disease datasets (Uci, 2009)

Dataset name	Class label considered as positive	No. of positive class instances	No. of negative class instances
H-O	0 (healthy)	165	138
Sick-1	1 (sick1)	56	247
Sick-2	2 (sick2)	37	266
Sick-3	3 (sick3)	36	267
Sick-4	4 (sick4)	14	289

3-3- Applicable Solution for the Proposed Methods

Data mining using analytical modeling, classification and data prediction method using related tools. In order to extract knowledge, data mining algorithms, requires a series of pre-processing and post-processing on the data and on extracted respectively (Rashedur, 2012). Since the used dataset has little records, in order to overcome the problem of over-training and under-training, database records are randomly displaced by randomize methods.

10 – Fold

First, based on table I, each sets used 10-fold cross validation, and classified with the above six algorithms. Here, the data set equally split in to 10 random sets. Then 90% of the data used for training and the rest for testing. In the next step, 10% of the data which used for testing in previous step, used for training and 10% of the 90% data which used for testing in pervious step, now used for testing.

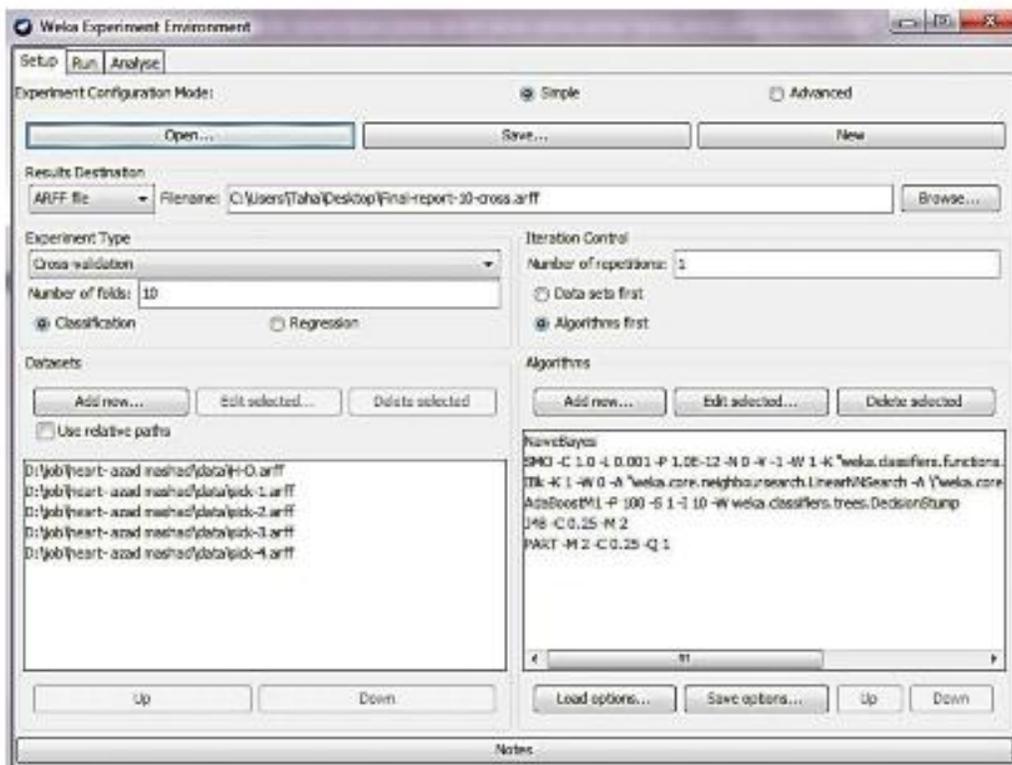


Figure 1.10:- Cross-fold Setup.

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This process repeats for 10 times. Modeling process in Weka come in the following:

- 1- Select the Experimenter button to enter testing aria in Weka. In order to enable options for the Experimenter, click on *New* button.
- 2- In this section we drop the *Cross Validation* option and set the number of repeats to 10 times.
- 3-Five data sets obtained in the previous step are loaded in this part. To do this, click on *Datasets* Options and data sets are selected one after another.
- 4- After selecting dataset in the part *Algorithm*, the mentioned models are selected from the *Add New* part. For example, to select the Naïve bayes, the *Add new* option must first be selected, and then in the top window they *Choose* option should be selected. *Bayes* folder should be selected from the *Classifier* available list and then selected *NaiveBayes* from the folder model.
- 5- After selecting the settings in this section, the storage location and file name of the model from the Setup tab at the top of the *Results Destination* window is selected so that after running the simulation results will be shown in this file.
- 6- Select the Run option in the next Tab and click the Start button to begin modeling.

To view the results of the modeling and do further investigations one must click on the *Analyse* tab and follow the following steps:

1. First, click on the *File* option and then select the file in the modeling report.
2. To choose an index on which models should be compared with, the *Comparison field* options must be clicked and the indicators are selected from the list of indicators. For example *Percent_correct* index represents the percentage of the correctly classified records or represented the accuracy of the model. All the indicators of the true positive rate forecasts (TP) and F index are in this section.
- 3.

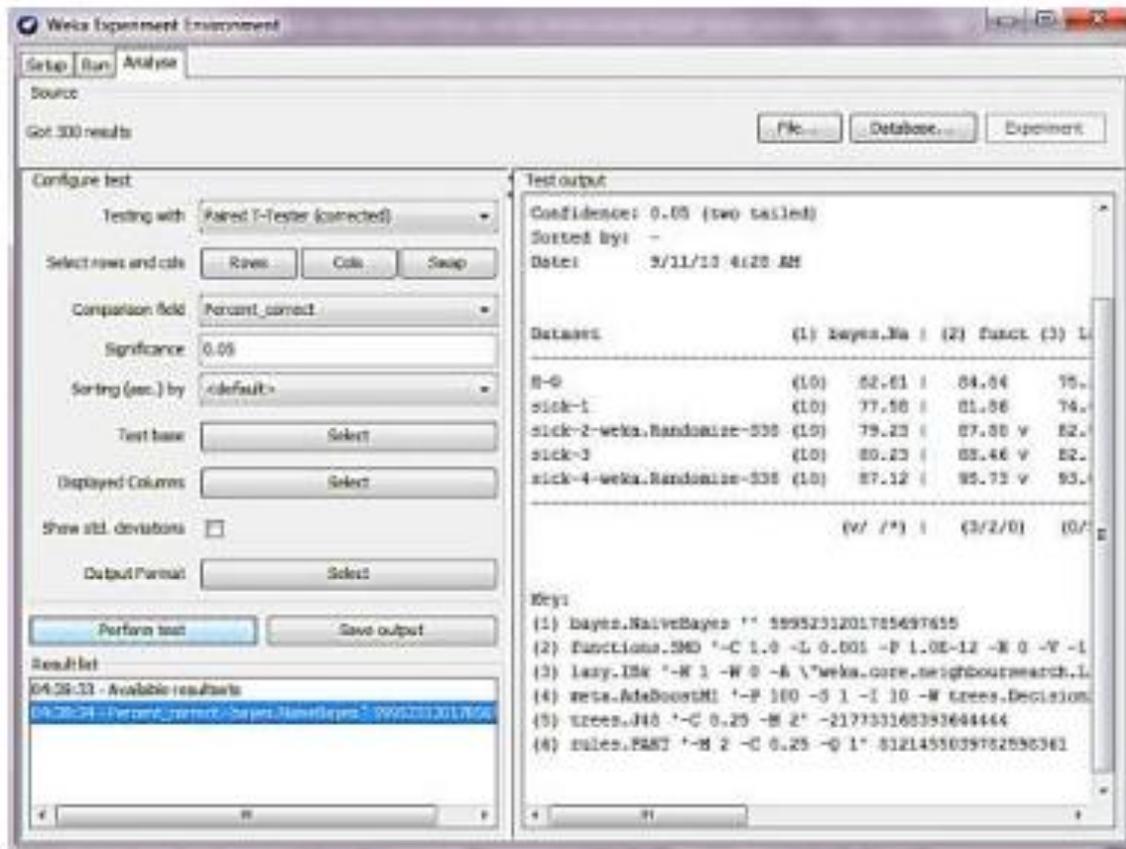


Figure 2: Analyse part

The results of the five main data validation modeling using 10-fold validation listed in Table II.

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3-4- CVP 10-fold

The first step is to set the records into two categories: training with two thirds of the data and testing with one third of the data.

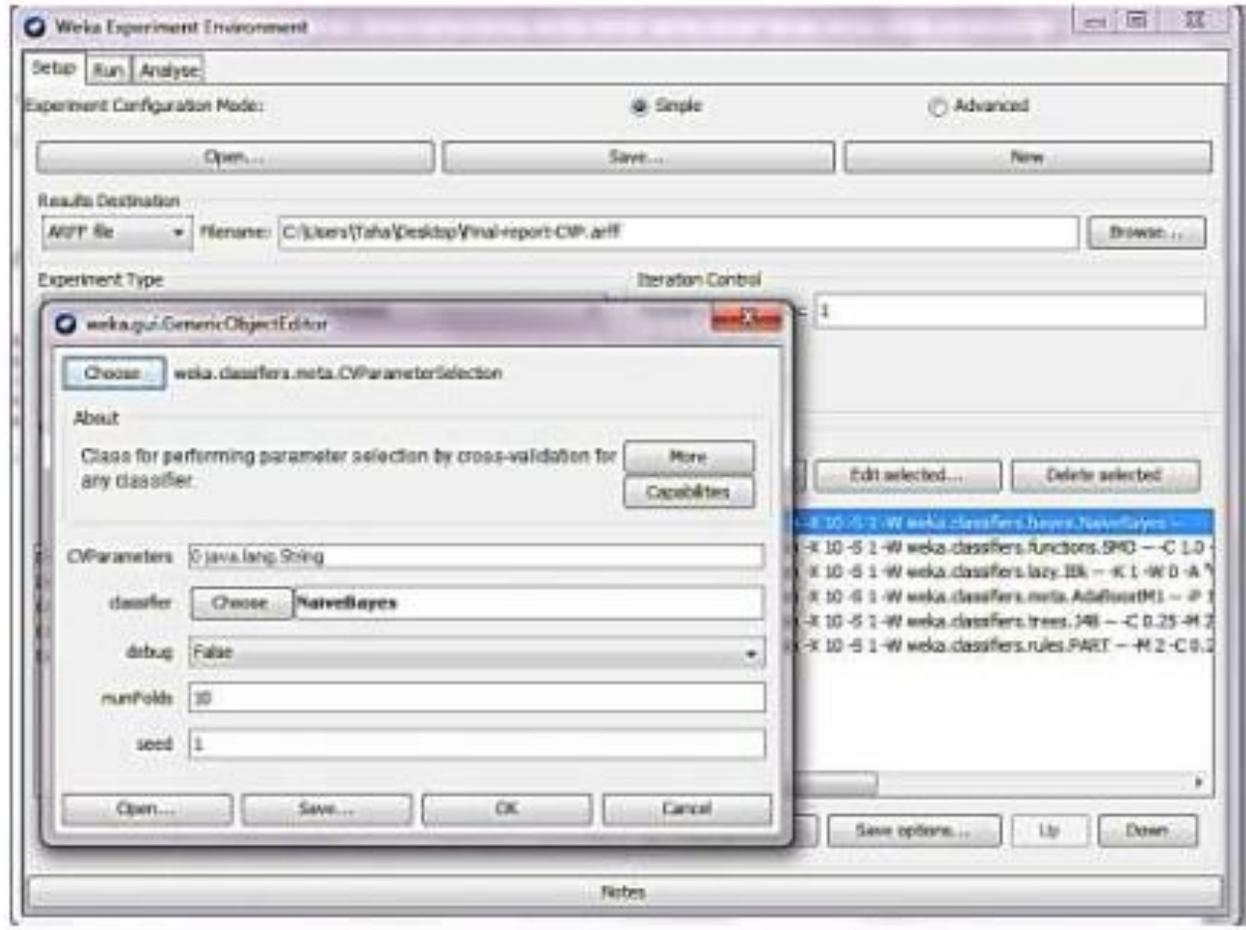


Figure 3: Setup part for CVparameter Setting

Then *CV parameter* methods have to be used for finding optimal parameters for each of the six classification methods with the help of 10-folding cross validation. *CV parameter* is in the folder of the Meta trainer in the classification methods.

To apply this method on each of the five datasets, following steps has been done in Weka:

- 1- Select the *Train / Test Percentage Split from the Experiment Type* option.
- 2- Default value of the *Train Percentage* is 66.0.
- 3- Data sets are selected according to the step three in the previous part.
- 4- In the algorithm section, click on the *Add New* button to open the *Choose Options* and choose *CV Parameter Selection* from the subfolder *Meta*. Then click on the *Classifier* to select the six classification algorithms. 10-fold validation settings can be changed but their default values are used.
- 5- Other steps in this section, including the steps mentioned in the previous step will be executed and the results of these indicators are intended to achieve.

The results of modeling on five main research datasets using CVparameter are listed in the column CVP in Table 2.

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Table 2: Results of Modeling

		Accuracy		TP		F-measure	
		10-fold	CVP	10-fold	CVP	10-fold	CVP
H-O	Naive Bayes	82.81	82.52	0.87	0.89	0.84	0.85
	SMO	84.84	82.52	0.9	0.86	0.87	0.84
	IBK	75.27	74.76	0.78	0.84	0.77	0.78
	AdaBoostM0	83.22	77.67	0.85	0.84	0.84	0.8
	J48	74.35	78.64	0.82	0.86	0.77	0.81
	PART	75.62	80.58	0.75	0.73	0.76	0.8
Sick-1	Naive Bayes	77.57	76.7	0.91	0.91	0.87	0.87
	SMO	81.86	82.52	1	1	0.9	0.9
	IBK	74.6	78.64	0.84	0.87	0.84	0.87
	AdaBoostM1	81.86	82.52	1	1	0.9	0.9
	J48	81.86	82.52	1	1	0.9	0.9
	PART	74.54	77.67	0.87	0.88	0.85	0.87
Sick-2	Naive Bayes	79.23	77.67	0.87	0.88	0.85	0.87
	SMO	87.8	88.35	1	1	0.93	0.94
	IBK	82.53	76.7	0.9	0.86	0.9	0.87
	AdaBoostM0	85.81	88.35	0.95	0.99	0.92	0.94
	J48	87.81	82.52	0.99	0.93	0.93	0.9
	PART	83.54	86.41	0.92	0.96	0.91	0.93
Sick-3	Naive Bayes	80.23	78.64	0.85	0.82	0.88	0.87
	SMO	88.46	88.35	1	1	0.94	0.94
	IBK	82.17	87.38	0.91	0.95	0.9	0.93
	AdaBoostM0	86.15	85.44	0.96	0.93	0.92	0.92
	J48	86.51	88.35	0.97	1	0.93	0.94
	PART	83.18	82.52	0.92	0.92	0.91	0.9
Sick-4	Naive Bayes	87.12	86.41	0.9	0.88	0.93	0.93
	SMO	95.73	96.12	1	1	0.98	0.98
	IBK	93.09	94.17	0.97	0.97	0.96	0.97
	AdaBoostM0	94.4	93.2	0.99	0.97	0.97	0.96
	J48	95.73	96.12	1	1	0.98	0.98
	PART	93.74	94.17	0.98	0.98	0.97	0.97

In this paper, SMO method used as the best method for heart disease diagnosis. But in Imam *et al.*, SMO was better only in three data sets. Since in this paper, the record has changed, the values of two indexes include TP and F-measure has increased dramatically.

Better result than the result of Near *et al.*, (2013) are bold in the above table.

3-5- Features Selection

In this article, features selection they are more effective in detecting heart disease have been selected by two methods. The first method is the use of medical knowledge based feature selection (MFS) which is based on the previous research in this area and the second method is based on the computer feature selection (CFS) with using the best searching strategy in Weka.

In this stage, the variables are selected on the basis of available medical knowledge.

They were determined according to the research study in a separate table (Nahar *et al.*, 2013). The following steps should be done for CFS implementation in Waka software.

1-First, choose *Select attributes* from the *Explorer* tab.

2-In the *Attribute Evaluator* or *evaluation criteria* select *choose* button and from options choose *CfsSubsetEval*.

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3- In the *Search Method* section, feature search should be specified for the CfsSubsetEval techniques. Best First method is used for features selection. Thus, Best First method is selected by clicking *Choose* button.

4- Right click on the *Start* button. After a few moments the result of feature selection, as shown in the following figure shows *Attribute selection*.

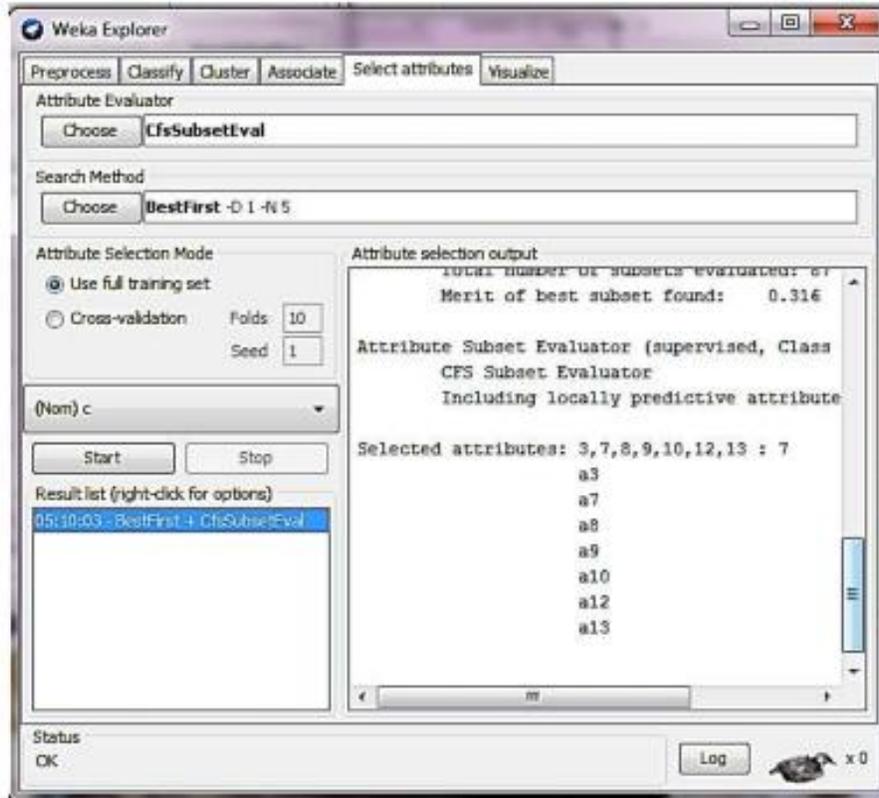


Figure 4: Select attributes part for feature selection.

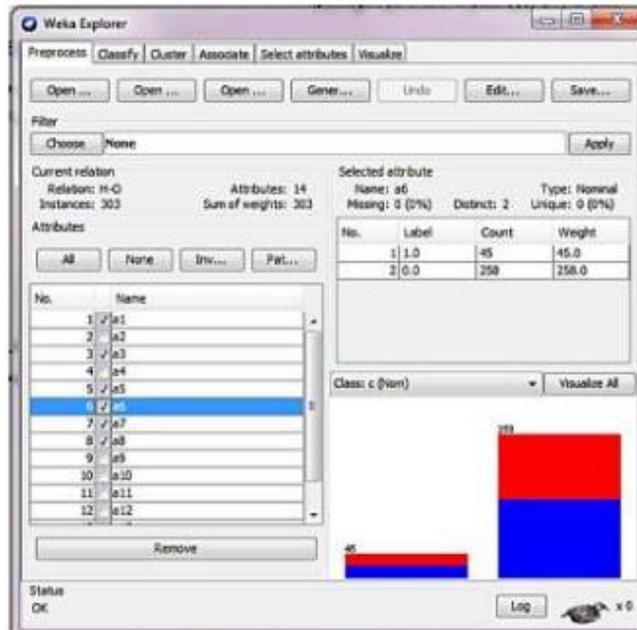


Figure 5: Manually selection of the variable

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Point: In order to select the variables manually from the *Preprocess* tab in *Explorer* and then by the buttons *Add* select the variables which are not selected yet, then select the *Save* option at the top of the window in order to save the changes.

Selected Variables by feature selection method based on MFS and CFS are available in five data sets.

(Nahar et al., 2013).

3-6-Modeling on the Set of Selected Variables

Here on each of the five data sets, modeling is done. By combining the selected variables, new variables which are agreed by both methods were produced. The table 3 shows the results of applying the model on five of the six data sets, each with three methods CFS, MFS and combination of these two approaches.

Table 3: Modeling on the selected variables

		Accuracy			TP			F-measure		
		CFS	MFS	MFS+CF S	CF S	MF S	MFS+CF S	CF S	MF S	MFS+CF S
H-O	Naive Bayes	83.9	74.2	83.01	0.88	0.76	0.87	0.86	0.76	0.85
	SMO	84.2	75.9	83.64	0.9	0.76	0.9	0.86	0.77	0.86
		2	1							
	IBK	77.6	70.4	74.34	0.82	0.73	0.78	0.8	0.73	0.77
		7	9							
	AdaBoostM	83.8	75.3	82.58	0.88	0.76	0.86	0.86	0.77	0.84
	0		5							
	J48	76.7	70.4	75.84	0.83	0.76	0.8	0.79	0.73	0.78
		8	3							
	PART	77.6	72.1	75.38	0.82	0.75	0.78	0.8	0.74	0.77
		6								
Sick -1	Naive Bayes	77.9	79.0	75.74	0.94	0.96	0.9	0.87	0.88	0.86
		6	3							
	SMO	81.8	81.8	81.86	1	1	1	0.9	0.9	0.9
		6	6							
	IBK	79.1	68.7	69.23	0.95	0.8	0.82	0.88	0.81	0.81
		8	6							
	AdaBoostM	81.8	81.8	81.86	1	1	1	0.9	0.9	0.9
	1	3	6							
	J48	81.8	81.8	81.86	1	1	1	0.9	0.9	0.9
		6	6							
	PART	80.8	77.7	72.28	0.99	0.95	0.86	0.89	0.87	0.83
		1	6							
Sick -2	Naive Bayes	79.9	80.8	79	0.85	0.9	0.84	0.88	0.89	0.87
			5							
	SMO	87.8	88.1	87.86	1	1	1	0.94	0.94	0.94
		6	3							
	IBK	84.1	79.4	83.93	0.92	0.88	0.92	0.91	0.88	0.91
			5							
	AdaBoostM	85.5	87.7	85.05	0.96	0.99	0.96	0.92	0.93	0.92
	0	8	3							

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Sick -3	J48	87.7 7	86.9 4	86.61	0.99	0.99	0.98	0.93	0.93	0.93
	PART	85.7 6	83.6 3	82.78	0.95	0.94	0.91	0.92	0.91	0.9
	Naive Bayes	81.9 8	85.4 9	81.8	0.87	0.93	0.86	0.89	0.92	0.89
	SMO	88.4 6	88.4 6	88.46	1	1	1	0.94	0.94	0.94
	IBK	83.8 5	79.6 5	82.65	0.94	0.89	0.9	0.91	0.88	0.9
	AdaBoostM0	86.6 1	87.7	86.48	0.95	0.99	0.96	0.93	0.93	0.93
Sick -4	J48	86.4 6	88	86.75	1	0.99	0.97	0.94	0.94	0.93
	PART	86.1 8	85.6 2	83.41	0.97	0.96	0.92	0.93	0.92	0.91
	Naive Bayes	94.8 3	94.1 5	91.62	0.98	0.98	0.94	0.97	0.97	0.96
	SMO	95.7 3	95.7 3	95.73	1	1	1	0.98	0.98	0.98
	IBK	94.1 8	92.6 9	92.36	0.98	0.96	0.96	0.97	0.96	0.96
	AdaBoostM1	95.5	95.6 7	95.14	0.99	1	0.99	0.98	0.98	0.97
	J48	95.7 3	95.7 3	95.73	1	1	1	0.98	0.98	0.98
	PART	95.7 3	94.8 4	94.44	1	0.99	0.99	0.98	0.97	0.97

The Proposed Method

In this step, in order to raise the accuracy of the models, decision was made to rise instead of dividing the data set into training and testing sets, 10 –fold validation method is used. And each model runs 10 times. So each model run 100 times and this result in increasing the validity of the models. The more difference results were marked. Validation of the data is one of the main reasons in this study. Most of the models produced by the three feature selection methods have TP and F-measure index equal to 0 on the main data sets in (Nahar *et al.*, 2013). This result shows the weakness of the proposed method in over learning and modeling but the validation of these indicators have increased dramatically.

Proposed Method for Better Evaluation

For a closer look, here, re-sample corrected T-test in order to show the difference between the performances of the optimized support vector machine algorithm (SMO) compared to the other used models. The test is applied based on three data sets CFS, MFS and MFS + CFS and according to the accuracy index. In fact, this test is looked for variance between the parameters of the models, (a six classification methods carried out on 5 datasets with 3 features selection methods that are $3 \times 5 \times 6 = 90$ models).

The following steps were implemented in Weka software:

1. The Experimenter was implemented.

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2. In the Analyse part, the output of the modeling on the five data sets which their variables were selected by three Feature selection methods mentioned above, were selected.
- 3- In the *Comparison field*, the *Percent_Correct* option was selected.
- 4-*Ranking* in the *Test base* option is selected and click on the option *Perform test*.

Table 4: The result of the re-sampling test of the corrected T-test

Method Name	Positive Difference	Negative Difference	Ranking
SMO	31	0	31
AdaBoostM1	24	0	24
J48	20	8	12
PART	3	19	-16
Naive Bayes	9	25	-16
IBK	0	35	-35

In this way, the values of the positive difference column in the table IV is equal to the number of the models that their accuracy index value are significantly less than the value of the model and the negative difference is the number of models that accurate indicator deal with more significantly difference. The difference between these two values is presented in the column rank or Rank. According to the obtained results in the table4, it is clear that the support vector SMO optimized algorithm significantly has a more appropriate accuracy indicator than the other method. On the other hand, IBK method is the worst method among the methods.

Conclusion

Here 6 classification algorithms were performed on the heart data set and in order to enhance the accuracy of the models, instead of dividing the data set into two categories of training and testing, 10-fold validation method is used. The models run 10 times so that each model run 100 times. This will increase the reliability of the models. The support vector optimized algorithm (SMO) significantly has a more appropriate accuracy indicator than the other method. On the other hand, IBK method is the worst method among the used methods.

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