Predicting the Likelihood of Heart Failure with a Multi Level Risk Assessment Using Decision Tree

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Abstract—**Heart failure comes in the top causes of death worldwide. The number of deaths from heart failure exceeds the number of deaths resulting from any other causes. Recent studies have focused on the use of machine learning techniques to develop predictive models that are able to predict the incidence of heart failure. The majority of these studies have used a binary output class, in which the prediction would be either the presence or absence of heart failure. In this study, a multi-level risk assessment of developing heart failure has been proposed, in which a five risk levels of heart failure can be predicted using C4.5 decision tree classifier. On the other hand, we are boosting the early prediction of heart failure through involving three main risk factors with the heart failure data set. Our predictive model shows an improvement on existing studies with 86.5% sensitivity, 95.5% specificity, and 86.53% accuracy.**

Keywords— heart failure; decision tree; prediction and classification; data mining

I. INTRODUCTION

Heart Failure (HF) is a serious condition and one of the leading causes of death worldwide [1]. According to the European Society of Cardiology (ESC), approximately 26 million adults globally are suffering from heart failure, 17% - 45% of these patients die within the first year and the remaining die within 5 years [2]. Heart failure is a public health problem with high societal and economic burdens. It is considered the main cause of frequent hospitalisations in individuals 65 years of age or older, and around 4.9 million Americans suffer from heart failure [3]. There is a lack of international consensus on a unified definition of heart failure and there are a variety of definitions in the literature. . However, the Scottish Intercollegiate Network Guideline (SIGN) has succinctly defined the chronic heart failure as "*A complex clinical syndrome that can result from any structural or functional cardiac or non-cardiac disorder that impairs the ability of the heart to respond to physiological demands for increased cardiac output.*" [4, 5].

In other words, the term 'heart failure' refers to a condition in which the heart is unable to pump a sufficient amount of blood around the body [2]. This condition occurs because of many potential causes, some are illnesses in their own right, whilst others can be perceived as the end stage of other underlying diseases [2, 3]. The majority cases of heart failure are secondary to coronary disease compared to other causative factors such as hypertension, valvular disease, myocarditis, diabetes, alcohol excess and obesity [3, 5].

Early prediction of heart failure has a significant impact on patient safety, as it can lead to an effective and possibly successful treatment before any serious degradation of cardiac output. In contrast, diagnosis of heart failure in a late stage severely limits the therapeutic benefits of interventions and the prospect of survival [2].

Applications of machine learning and data mining techniques can be applied to allow early detection of heart failure. These techniques can effectively diagnose heart failure at an earlier stage by extracting valuable information from the patient data sets [6, 7]. In recent years, there has been a dramatic increase in the use of machine learning techniques to analyse, predict and classify medical data. The concept of machine learning refers to a computer system that is able to learn the important features of a given dataset in order to make predictions about other data that were not part of the original training set [8]. These types of systems can learn and gain knowledge from past experiences and/or through identifying patterns in the medical data [9]. Computer based classification can utilise machine learning approach, which aims to separate a given dataset into two or more classes based on attributes measured in each instance of that dataset. It has achieved impressive results in many real world fields. Within the healthcare sector, classification can be used for medical data analysis to predict or diagnose a particular disease, or assess the impact of an intervention [10, 11].

More recently, the decision tree classifier has been widely used in a range of studies [14, 15, 16, 17, 18, 19 20, 21] to predict heart failure. Usually, it is used with a binary output class, in which the prediction would be either the presence or absence of heart failure. Several previous studies that employed decision tree approaches are reviewed in the related work section. The majority of them have used the same heart disease dataset, which is published online at [13], and has shown different classification accuracy with some proposed

enhancement methods. The current study has targeted the improvement of dataset features by involving some of risk factors that have a noticeable role in increasing the likelihood of developing heart failure. We have extended the utility of the decision tree approach by utilising multiple output classes, in which the prediction would be one of five risk levels.

Within this paper, we aimed to: a) review many related studies that have used the same dataset of heart disease that have been published online at [13]; b) improve the early prediction of heart failure by the inclusion of three extra features; c) predict the likelihood of developing heart failure with five risk levels using the C4.5 decision tree classifier with multi output classes; and d) evaluate the proposed method by comparison with the results obtained from previous studies.

II. STUDY CONTRIBUTION

This study holds two principal contributions, which have previously been reported. The first contribution is to improve the early prediction of heart failure by involving three main risk factors within the same dataset available at [13]. We are concentrating on improving dataset characteristics of heart failure through adding three additional features, which are obesity, smoking and physical exercise. These features have not been included within the original dataset, and would potentially improve the timely prediction accuracy. According to several studies [2, 3, 4], these factors could dramatically increase the likelihood of heart failure. It is estimated that a 30% reduction in the proportion of obese people would prevent around 44,000 cases of heart failure each year in the USA [2]. Being obese has been shown to double the risk of heart failure, while smoking increases heart failure by about 50%. Hence, these two risk factors are major contributors to the heart failure epidemic [2, 3]. Physical exercise is linked to longevity, independently of genetic factors. As published by the world health organization (WHO), exercise can greatly reduce many risk factors even at an older age, such as heart failure, high blood pressure, diabetes and obesity. Moreover, exercise assists in reducing stress, and depression along with improving lipid profile [12].

The second contribution is the use of C4.5 decision tree classifier with multi output class to predict five risk levels of heart failure, namely no-risk, low, moderate, high and extremely high-risk of heart failure. This is more precise than a binary classification method (i.e. the presence of heart failure or not). It has the potential to enhance decision making for healthcare providers by providing additional and earlier information leading to the timely provision of a suitable care plan based on the risk level. This stratification would distinguish amongst the levels of care provided to patients according to their needs, as some of them might need more intensive care, whilst others could be managed by changing their lifestyle through lifestyle interventions such as improving diet, increasing physical activity and stopping smoking.

III. RELATED WORKS

This section reviews a range of recent studies that aims to predict heart failure. The majority of these studies used the same dataset of heart disease, which is published online at [13],

the remaining minority were not. Different types of decision tree techniques have been used within these studies along with some proposed improvement. However, they are followed approximately the same evaluation methods by measuring the sensitivity, specificity and accuracy of a given classifier.

In [14], Pandey and his colleagues have developed a prediction model for heart disease using the mentioned dataset in [13] and J48 decision tree classifier. Using a holdout validation method, the data set was divided into a training set with 200 instances and testing set with 130 instances. The aim was to develop an accurate and small decision rule. This has been achieved by applying reduced error pruning methods. Obtained results showed that the pruned J48 decision tree with reduced error pruning method has reached 75.73% of accuracy.

Bashir et al. [15] proposed the use of majority vote from three different classifiers namely Naïve Bayes, Decision Tree and Support Vector Machine for heart disease diagnosis. The dataset available at [13] was used for the experiment. Each classifier was individually trained using training set. Obtained decisions from these three classifiers, then combined them based on majority voting scheme. 81.82% of accuracy has shown by the proposed framework with two output classes.

Chaurasia and Pal have used the commonest types of decision tree algorithms for the prediction of heart diseases in [16]. CARD, ID3 and DT decision trees were applied with the same dataset available at [13], and evaluated using 10-fold cross validation method. CARD decision tree has presented the highest classification accuracy with 83.49%, followed by DT with 82.50% and finally 72.93% for ID3.

Uppin et al. [17] have implemented C4.5 decision tree classifier for predicting heart disease. The data set in [13] were also used within this experiment. Their strategy aimed to reduce the number of parameters within the data set in order to avoid the redundant features that are not important in the classification. Therefore, 7 of 13 parameters have only been used and the C4.5 classifier showed 85.96% of accuracy.

Mahmood and Kuppa [18] proposed a new pruning method with the aim of improving classification accuracy of heart diseases and reducing the tree size. A combination of pre-pruning and post-pruning was used for pruning C4.5 decision tree classifier. The new decision tree has been compared with the benchmark algorithms using dataset available online at [13]. The results showed that the new method significantly reduced the tree size and achieved 76.51% of accuracy.

Shouman et al [19] were focusing on the improvement of decision tree accuracy for diagnosis of heart disease. K-means clustering was integrated into the decision tree in order to enhance the diagnosis of heart disease. The dataset mentioned in [13] has been utilised. The highest accuracy obtained was 83.9% by applying the inlier method with two clusters.

Bohacik et al [20] applied an alternating decision tree for the prediction of heart failure. In this type of decision tree, each part can be split multiple times rather than only leaf nodes. This is because a weighted error of the added rule is used as a splitting criterion. A heart failure dataset derived from Hull LifeLab with 9 attributes and 2 prediction classes. The

alternating decision tree showed 77.65% of classification accuracy using 10-fold cross validation method.

Melillo et al [21] developed a model for risk assessment in patients suffering from congestive heart failure. ECG recording for long-term heart rate variability has been used as a dataset, which is derived from two different Congestive Heart Failure databases. A CART decision tree algorithm is used with the aim of classifying patients into two groups based on the risk factor, and achieved 85.4% of accuracy.

IV. DECISION TREE CLASSIFIER

Decision tree is a schematic illustration of the relations that exist between the dataset [22], which will presented treelike structure "Fig. 1". It is a supervised automatic learning technique that can handle both classification and regression tasks. It is simple, yet powerful method of representing knowledge [22, 23]. It uses the training set of instances that represented by a number of attributes to derive the rules, which can be interpreted in a straightforward manner [23]. Decision tree sorts instances according to the attribute values, each attribute in an instance to be classified represents as a node, and each branch represents a value that the node can predict. Instances are classified starting from the root node and following the argument down based on their attribute values until it reaches the final node.
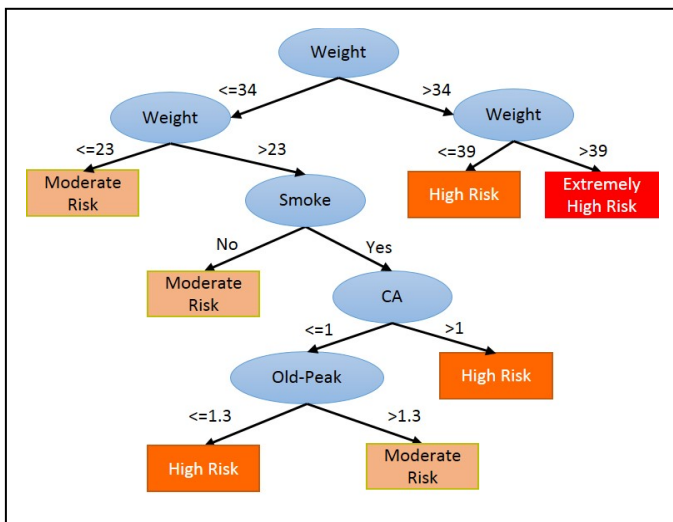

Fig. 1. Decision tree classifier

Generally, decision trees can easily translated into a particular set of rules, where each standalone path from the root node to a certain leaf node can produce a particular rule [22, 24]. The decision tree algorithm is a well-known classification technique that used in several problem domains, including medical diagnosis, classification problems, marketing, fraud detection and so on [23]. There are several types of decision tree classifier such as ID3, CART and C4.5. The difference among them is the mathematical model that employed in the splitting of the attributes. The most common models used for splitting are Information Gain, Gini Index, and Gain Ratio.

V. EXPERIMENTAL STUDY AND RESULTS

A. The used data set

The Cleveland Clinic Foundation heart disease dataset has been used in this study, which is available online at [13]. It consists of 297 consistent instances and without missing values. Each instance contains 13 attributes in addition to the output class, 53.87% of the instances are for patients with no risk of developing a heart failure, while the remaining 46.13% are for patients with different risk levels. Details of the heart failure dataset are presented in Table 1.

TABLE I. HEART FAILURE DATA SET WITH 13 ATTRIBUTES

No.	Attributes	Types	Descriptions
1	Age	Continuous	Age in years
2	Sex	Discrete	Gender (1: male and 0: female)
3	CP	Discrete	Chest pain 1: typical angina 2: atypical angina 3: non-anginal pain 4: asymptomatic
4	Trestbps	Continuous	Resting blood pressure in mm Hg
5	Chol	Continuous	Serum cholesterol in mg/dl
6	Fbs	Discrete	Fasting blood sugar > 120 mg/dl 1:true 0:false
7	Restecg	Discrete	Resting electrocardiography results 0: normal 1: having ST-T wave abnormality 2: left ventricular hypertrophy
8	Thalach	Continuous	Maximum heart rate
9	Exang	Discrete	Exercise induced angina (1: yes and 0: no)
10	Oldpeak	Continuous	Depression induced by exercise relative to rest
11	Slope	Discrete	The slope of the peak exercise ST segment 1: up sloping 2: flat 3: down sloping
12	Ca	Discrete	Number of major vessels coloured by fluoroscopy (from 0 to 3)
13	Thal	Discrete	3: normal 6: fixed defect 7: reversible defect
14	Class	Discrete	The predicted attributes 1: No risk 2: Low risk 3: Moderate risk 4: High risk 5: Extremely high risk

As described previously, our goal is to improve the early prediction of heart failure by enhancing the dataset features. Therefore, three new attributes (i.e. risk factors) have been added within the dataset namely obesity, physical activity and smoking. These attributes have not been involved within the same dataset before, and they hold a significant role to increase the likelihood of heart failures. The newly added attributes are explained in Table 2.

TABLE II.   THE NEWLY ADDED RISK FACTORS

No.	Attributes	Types	Descriptions
1	Obesity	Continuous	The Body Mass Index (BMI) used for measurements.
2	Smoking	Discrete	1: Yes 2: No
3	Physical exercise	Discrete	General physical activities such as gym, cycling, walking etc. 1: Yes 2: No

After adding the three risk factors to the main dataset, the new dataset would be represented as a set S = {<age_1, sex_1, cp_1, $trestbps_1$, $chol_1$, fbs_1, $restecg_1$, $thalach_1$, $exang_1$, $oldpeak_1$, $slope_1$, ca_1, $thal_1$, $weight_1$, $smoke_1$, $exercise_1$>,...,<age_n, sex_n, cp_n, $trestbps_n$, $chol_n$, fbs_n, $restecg_n$, $thalach_n$, $exang_n$, $oldpeak_n$, $slope_n$, ca_n, $thal_n$, $weight_n$, $smoke_n$, $exercise_n$>}. The size of the set S is n, which is the total number of instances. The attributes are defined as A = {A_1; …; A_k}. If A_k is discrete attribute, A_k = {$a_{k,1}$; ...; $a_{k,y}$} , where $a_{k,1}$ and $a_{k,y}$ are possible discrete values. Class attribute is used to classify heart failure patients into five risk levels, class label represented as C = {c_1,…,c_m}, in this study m=5 and C = {no risk; low risk; moderate risk; high risk; extremely high risk}.

B. Validation Method

In order to examine the overall performance of the decision tree classifier, the 10-fold cross-validation method is used to measure the classifiers' performance. This method is usually utilised to maximise the use of the data set. The data set is randomly partitioned into 10 equal subsets. Each one of them contains approximately the same proportion of different class labels. Of the 10 subsets, a single subset is retained as a testing data, and the remaining 9 subsets as the training data. The cross-validation process is then repeated 10 times, until each one of the 10 subsets was used exactly once as a testing set "Fig. 2". The results can then be averaged to estimate the classifier's performance. The advantage of this method is that all subsets are used for both training and testing, and each subset is used for testing exactly once [25, 26].
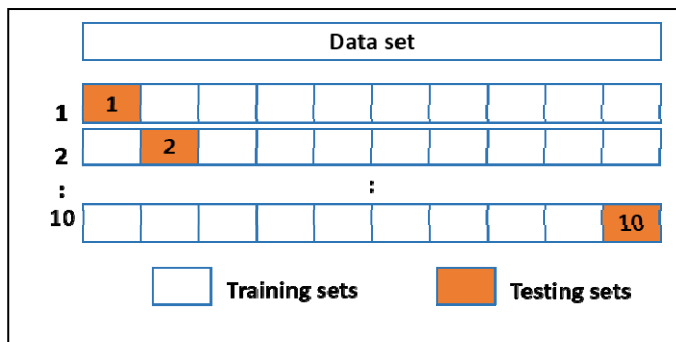

Fig. 2. 10-fold cross validation method

C. Classifier Assessment

The overall performance of the predictive model for heart failure risk assessment can be calculated using a range of statistical methods including sensitivity, specificity and accuracy [26]. These calculations can be made based on the numbers of a correctly and incorrectly predicted risk levels, which are presented in the confusion matrix as integer values [27]. The confusion matrix plots the true class of instances (i.e. gold standard) in a classification problem against the predicted class, which generated by the predictive model. These will be represented as true positive (TP), false positive (FP), true negative (TN) and false negative (FN) [26, 27].

Let's consider that (A, B, C, D and E) are matched (No, Low, Moderate, High and Extremely High) risk levels respectively. Then the following Table 3 presents the confusion matrix of the heart failure predictive model.

TABLE III.   THE CONFUSION MATRIX OF THE PREDICTIVE MODEL

		Predicted classes				
		A	B	C	D	E
Actual classes	A	146	0	14	0	0
	B	0	32	0	3	0
	C	18	0	36	0	0
	D	0	5	0	30	0
	E	0	0	0	0	13

Where, sensitivity and also called the true positive rate (TPR), refers to the classifier's ability to identify a risk level correctly, while the specificity refers to the classifier's ability to exclude the other risk levels correctly (identifies the negative cases). The classification accuracy is the overall correctness of the model, it can be calculated as the sum of true results (both true positives and true negatives) divided by the total number of the examined test set [25, 26]. The sensitivity, specificity, precision and accuracy of a multi output classification problem can be expressed mathematically as follows:

$$Sensitivity = \frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l}(TP_i + FN_i)}$$

$$Specificity = \frac{\sum_{i=1}^{l} TN_i}{\sum_{i=1}^{l}(TN_i + FP_i)}$$

$$Precision = \frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l}(TP_i + FP_i)}$$

$$Accuracy = \frac{\sum_{i=1}^{l} \frac{TP_i + TN_i}{TP_i + FN_i + FP_i + TN_i}}{l}$$

D. Results and Discussion

Roughly three hundred instances are used in this experiment, which derived from the Cleveland Clinic Foundation heart disease dataset [13]. Among these instances, 53.87% were for healthy individuals with no likelihood of developing heart failure, while the remaining 40.07% was for patients with different risk levels. The major contribution of this study is to adopt a multi-level predictive model that is able to early predict the likelihood of developing heart failure using C4.5 decision tree classifier. In contrast to previous studies, a five different risk levels of heart failure can be predicted in this model. The following Table 4 illustrates the detailed

performance of each class using 10-fold cross validation method.

TABLE IV.   DETAILED PERFORMANCE OF THE PREDICTIVE MODEL

Output Classes	Sensitivity	Specificity	Precision	F-Measure	ROC Area
A	0.913	0.868	0.89	0.901	0.906
B	0.914	0.980	0.865	0.889	0.966
C	0.667	0.942	0.72	0.692	0.83
D	0.857	0.988	0.909	0.882	0.966
E	1	1	1	1	1
Average	0.865	0.955	0.863	0.864	0.91

As can be seen from the above table, the highest ability of detecting a risk level (i.e. sensitivity) was achieved by class E, which is the extremely high risk level of developing heart failure. This is considered an effective result because this level is the most threatening level and a proper decision can save a patient's life. Followed by class B that indicates to the first risk level of developing heart failure. Then class A that refers to healthy individuals with excluding all risk levels. While the lowest sensitivity was in detecting the moderate risk level (i.e. class C). This is due to the fact that this stage describes the shift from low risk ratio to a higher level and starting a serious threat that could possibly lead to death. The detailed results are shown in the following "Fig. 3".
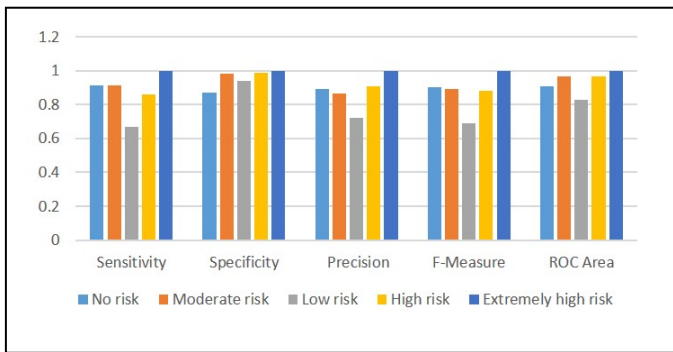

Fig. 3.   Detailed results of each class

In contrast to the previous models, our predictive model shows an impressive results with 86.53% of accuracy in predicting five different risk levels of heart failure using C4.5 decision tree. The following Table 5 illustrates our predictive model against nine other models.

TABLE V.   A COMPARISON OF DIFFERENT MODELS

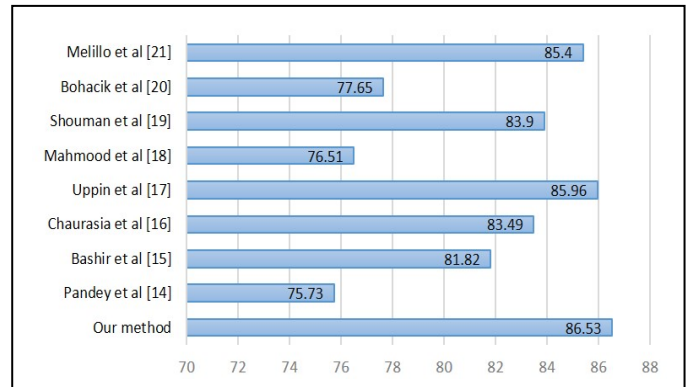|	Authors	Techniques	Output Classes	Accuracy
1	Our method	C4.5 Decision Tree	5	86.53%
2	Pandey [14]	Decision Tree with Reduced Error Pruning Method	2	75.73%
3	Bashir [15]	A combination of Naïve Bayes, Decision Tree and Support Vector Machine	2	81.82%
4	Chaurasia [16]	CARD Decision Tree	2	83.49%
5	Uppin [17]	C4.5 Decision Tree	2	85.96%
6	Mahmood [18]	C4.5 Decision Tree with New Pruning Method	2	76.51%
7	Shouman [19]	K-means Clustering and Decision Tree	2	83.9%
8	Bohacik [20]	Alternating decision tree	2	77.65%
9	Melillo [21]	CARD Decision Tree	2	85.4%

Fig. 4.   The accuracy of the predictive models

As showed in "Fig. 5", our method overcomes other methods that used decision tree in the prediction of heart failure due to three main reasons;

- Our method is able to predict five risk levels of heart failure namely no risk, low, moderate, high and extremely high risk of heart failure. This is more precise than methods with two output classes, which is the presence of heart failure or not.

- It showed a considerably higher classification accuracy than other methods using the same dataset in [13], and

- It takes into consideration three possible risk factors that increase the incidence of heart failure, which are obesity, lack of physical activity and smoking.

VI.   CONCLUSION AND FUTURE WORK

Using an open source data set of heart diseases that available online at [13], this paper presents a predictive model for multi-level risk prediction of developing heart failure using C4.5 decision tree classifier. The dataset features have been improved by adding three new features (i.e. risk factors), in order to improve the prediction accuracy. 10-fold cross validation method have been applied to a performance evaluation. Statistical measurements (i.e. sensitivity, specificity, accuracy) were used to evaluate the predictive model. The predictive model overcomes many other models with 86.5% sensitivity, 95.5% specificity, and 86.53% accuracy. The future trend would be towards engaging various other risk factors that increase the chance of developing heart

failure. On the other hand, improving the predictive model through utilising a certain feature selection method.

REFERENCES

[1] World Health Organization (WHO), "The top 10 causes of death, Fact sheet", Available at: http://www.who.int/mediacentre/factsheets/fs310/en/, Accessed in: 5 March 2015.

[2] European Society of Cardiology, "Heart failure: Preventing disease and death worldwide", Available at: http://www.escardio.org/communities/HFA/Documents/whfa-whitepaper.pdf, Accessed in: 5 March 2015.

[3] VL. Roger, "The heart failure epidemic", International Journal of Environmental Research and Public Health, 7(4), 1807-1830; doi:10.3390/ijerph7041807. 2010.

[4] C. Ward, "Introduction", Chapter one in book entitled: "A practical guide to heart failure in older people", John Wiley & Sons, 2009.

[5] Scottish Intercollegiate Guidelines Network (SIGN), "Management of chronic heart failure: A national clinical guideline", Available at: http://sign.ac.uk/pdf/sign97.pdf, Accessed in: 2 March 2015.

[6] T. Mythili, D. Mukherji, N. Padalia, and A. Naidu, "A heart disease prediction model using SVM-Decision Trees-Logistic Regression (SDL)", International Journal of Computer Applications, vol. 68, no.16, April 2013.

[7] M.A. Jabbar, B.L. Deekshatulu, and P. Chndra, "Alternating decision trees for early diagnosis of heart disease" Proceedings of International Conference on Circuits, Communication, Control and Computing (I4C), India, IEEE, 2014.

[8] K.R. Foster, R. Koprowski and J.D. Skufca, "Machine learning, medical diagnosis, and biomedical engineering research commentary", BioMedical Engineering OnLine, 2014.

[9] A.J. Aljaaf, D. Al-Jumeily, A.J. Hussain, P. Fergus, M. Al-Jumaily and K. Abdel-Aziz, "Toward an Optimal Use of Artificial Intelligence Techniques within a Clinical Decision Support System", The Science and Information (SAI), London, 2015.

[10] S.H. El-Sappagh, S. El-Masri, A.M. Riad, and M. Elmogy, "Data Mining and Knowledge Discovery: Applications, Techniques, Challenges and Process Models in Healthcare", International Journal of Engineering Research and Applications (IJERA), vol. 3, issue 3, 2013.

[11] D. Foster, C. McGregor and S. El-Masri, "A Survey of Agent-Based Intelligent Decision Support Systems to Support Clinical Management and Research", First international workshop on multi-agent systems for medicine, computational biology, and bioinformatics, MAS*BIOMED'05, Netherlands, 2005.

[12] World Health Organization (WHO), "Risk factor: Physical inactivity", Available at: http://www.who.int/cardiovascular_diseases/en/cvd_atlas_08_physical_ inactivity.pdf, Accessed in: 5 March 2015.

[13] Cleveland Clinic Foundation, "Heart Disease Data Set ", Available at: http://archive.ics.uci.edu/ml/datasets/Heart+Disease, Accessed in: 7 March 2015.

[14] A.K. Pandey, P. Pandey, K.L. Jaiswal, and A.K. Sen, "A heart disease prediction model using decision tree", IOSR Journal of Computer Engineering (IOSR-JCE), vol. 12, Issue 6, PP 83-86, Aug. 2013.

[15] S. Bashir, U. Qamar, and M.Y. Javed, "An ensemble based decision support framework for intelligent heart disease diagnosis", International Conference on Information Society (i-Society 2014), London, IEEE, 2014.

[16] V. Chaurasia and S. Pal, "Early prediction of heart diseases using data mining techniques" Caribbean Journal of Science and Technology, vol.1, 208-217, 2013.

[17] S.K. Uppin, and M.A. Anusuya, "Expert system design to predict heart and diabetes diseases", International Journal of Scientific Engineering and Technology, vol. 3, no.8, pp: 1054-1059, 2014.

[18] A. M. Mahmood and M. R. Kuppa, "Early detection of clinical parameters in heart disease by improved decision tree algorithm", 2010 Second Vaagdevi International Conference on Information Technology for Real World Problems, Warangal, IEEE, 2010.

[19] M. Shouman, T. Turner and R. Stocker, "Integrating decision tree and k-means clustering with different initial centroid selection methods in the diagnosis of heart disease patients", Proceedings of the International Conference on Data Mining, 2012.

[20] J. Bohacik, C. Kambhampati, D.N. Davis and G.F. John, "Alternating decision tree applied to risk assessment of heart failure patients", Journal of Information Technologies, vol. 6, no. 2, 2013.

[21] P. Melillo, N.D. Luca, M. Bracale and L, Pecchia, "Classification tree for risk assessment in patients suffering from congestive heart failure via long-term heart rate variability", IEEE Journal of Biomedical and Health Informatics, vol. 17, issue 3, 2013.

[22] B. Milovic, and M. Milovic, "Prediction and Decision Making in Health Care using Data Mining", International Journal of Public Health Science (IJPHS), vol. 1, no. 2, 2012.

[23] D.R. Amancio, C.H. Comin, D. Casanova, G. Travieso, O.M. Bruno, F.A. Rodrigues and L.F. Costa," A Systematic Comparison of Supervised Classifiers", PLoS ONE 9(4): e94137, doi:10.1371/journal.pone.0094137, 2014.

[24] S.B. Kotsiantis, "Supervised Machine Learning: A Review of Classification Techniques", Informatica 31, 249-268, 2007.

[25] F.R. Silva, V.G. Vidotti, F. Cremasco, M. Dias, E.S. Gomi, and V.P. Costa, "Sensitivity and specificity of machine learning classifiers for glaucoma diagnosis using Spectral Domain OCT and standard automated perimetry", Arq. Bras. Oftalmol, vol. 76, no. 3, 2013.

[26] N. Gupta, A. Rawal, V.L. Narasimhan and S. Shiwani, "Accuracy, Sensitivity and Specificity Measurement of Various Classification Techniques on Healthcare Data", IOSR Journal of Computer Engineering (IOSR-JCE), vol. 11, issue 5, 2013.

[27] C. Elkan, "Evaluating Classifiers", Available at: http://cseweb.ucsd.edu/~elkan/250Bwinter 2012/classifiereval.pdf, Accessed in: 10 March 2015.