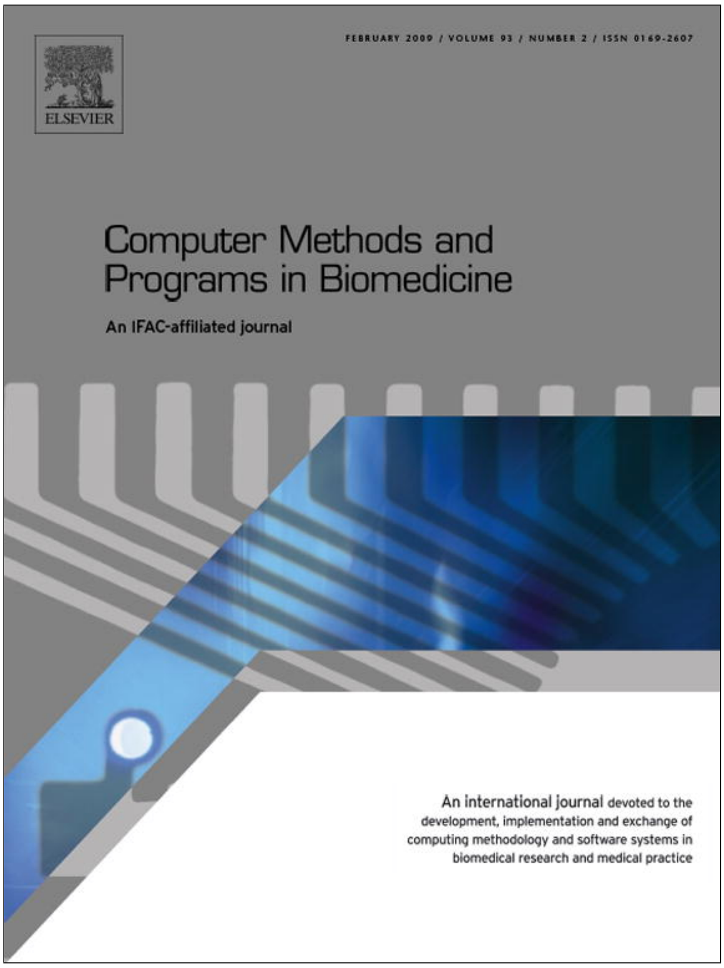
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Diagnosis of valvular heart disease through neural networks ensembles

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ABSTRACT

In the last decades, several tools and various methodologies have been proposed by the researchers for developing effective medical decision support systems. Moreover, new methodologies and new tools are continued to develop and represent day by day. Diagnosing of the valvular heart disease is one of the important issue and many researchers investigated to develop intelligent medical decision support systems to improve the ability of the physicians. In this paper, we introduce a methodology which uses SAS Base Software 9.1.3 for diagnosing of the valvular heart disease. A neural networks ensemble method is in the centre of the proposed system. The ensemble-based methods creates new models by combining the posterior probabilities or the predicted values from multiple predecessor models. So, more effective models can be created. We performed experiments with proposed tool.

We obtained 97.4% classification accuracy from the experiments made on data set containing 215 samples. We also obtained 100% and 96% sensitivity and specificity values, respectively, in valvular heart disease diagnosis.

1. Introduction

The dysfunction or abnormality of one or more of the heart's four valves (the mitral valve and aortic valve on the left side, and the tricuspid valve and pulmonic valve on the right side) is called valvular heart disease [1]. In a normally functioning heart, the four valves keep blood flowing in one direction and only at the right time. These valves act as gates that swing open to allow blood to flow through and then tightly shut until the next cycle begins [1].

According to the American Heart Association's 2006 Heart and Stroke Statistical Update, valvular heart disease is responsible for nearly 20,000 deaths each year in the United States and is a contributing factor in about 42,000 deaths [2]. The majority of these cases involve disorders of the aortic valve (63%) and the mitral valve (14%). Deaths due to pulmonic and tricuspid valve disorders are rare (0.06% and 0.01%, respectively).

There are a number of types of valvular heart disease, including; valvular stenosis, valvular regurgitation, atresia of one of the valves and mitral valve prolapse [1]. The diagnosis of valvular heart disease is usually performed by one of the following tests: physical examination may reveal a murmur, evidence of heart enlargement and fluids within the lungs. An electrocardiogram may reveal arrhythmias and chamber enlargement. Echocardiography and a Doppler ultrasound are the most widely used methods, and are very useful in assessment of presence and severity of valve disease. MRI can provide clear three-dimensional images of the heart and its valves.

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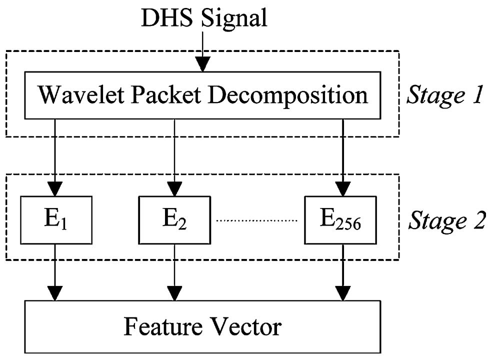

Fig. 1 – The structure of feature extraction.

Doppler technique has gained much more interest since Satomura first demonstrated the application of the Doppler effect to the measurement of blood velocity in 1959 [3]. Doppler heart sounds (DHS) are one of the most important sounds produced by blood flow, valves motion and vibration of the other cardiovascular components [4]. However, the factors such as calcified disease or obesity often result in a diagnostically unsatisfactory Doppler techniques assessment and, therefore, it is sometimes necessary to assess the spectrogram of the Doppler shift signals to elucidate the degree of the disease [4]. In addition to Doppler techniques, the techniques that are more complex have also been developed (Laplace Transform and Principal Components Analysis). Many studies have been implemented to classify Doppler signals in the pattern recognition field [5,6].

Recent advances in the field of artificial intelligence have led to the emergence of expert systems for medical applications. Moreover, in the last few decades computational tools have been designed to improve the experiences and abilities of physicians for making decisions about their patients. Motivated by the need of such an expert system, in this study, we propose a method to efficiently diagnose the valvular heart disease. The proposed method uses ensembles of neural networks as classifier. Ensemble-based methods enable an increase in generalization performance by combining several individual neural networks train on the same task. The performance of the proposed methodology was evaluated with several statistical validation methods. Moreover, we compared our results with the results of the previous methods where the same data set have been used. We obtained 97.4% classification accuracy from the experiments made on data set containing 215 samples. Our system also obtained 100% sensitivity and 96% specificity rate. This classification accuracy is the highest so far.

The rest of the paper is organized as following: in Section 2, a brief overview on previous related works, feature extraction and construction of the database and the ensemble-based methodology is described. The proposed methodology and the implementation with SAS base software are described in Section 3. The effectiveness of the proposed method for classification of Doppler signals in the diagnosis of heart valve diseases is demonstrated in Section 4. Finally, we concluded this paper in Section 5.

2. Background

2.1. *Related works*

Up to now, various classification algorithms have been employed on Turkoglu's valvular heart disease data set and high classification accuracies have been reported in the last decade [7–13]. Turkoglu's valvular heart disease data set was obtained from Firat Medical Center. A detailed description for the data set will be given in the next section.

The valvular heart disease data set was firstly utilized in ref. [7] where Turkoglu et al. fulfilled an expert diagnosis system which uses back-propagation artificial neural networks (BP-ANN) classifier. The performance evaluation of the realized system was evaluated by classification accuracy and the correct classification rate was about 94% for normal subjects and 95.9% for abnormal subjects. Later, Turkoglu et al. suggested an intelligent system for detection of heart valve disease based on wavelet packet neural networks (WPNN) [8]. The reported correct classification rate was about 94% for abnormal and normal subjects. Recently, Comak et al. investigated the use of least-square support vector machines (LS-SVM) classifier for improving the performance of the Turkoglu's proposal [9]. They intended to realize a comparative study. Classification rates of the examined classifiers were evaluated by ROC curves based on the terms of sensitivity and specificity. The application results showed that according to the ROC curves, the LS-SVM classifier performance was comparable with ANN, but the training time of LS-SVM is shorter than that of the ANN and it can always converge the same solution while ANN cannot. According to these results, LS-SVM's training time is about 13 times shorter than ANN's training time. This is an important difference. Because, LS-SVMs are trained only depending on support vectors, not by whole training data set. In addition, LS-SVM can overcome the overfitting much successfully than ANN.

More recently, Uguz et al. performed a biomedical system based on Hidden Markov Model for clinical diagnosis and recognition of heart valve disorders [10]. The fulfilled methodology was also used the database of Turkoglu et al. In the presented study, continuous HMM (CHMM) classifier system was used. Single Gaussian model was preferred to determine emission probability. The methodology was composed of two stages. At the first stage, the initial values of average and standard deviation were calculated by separating observation symbols into equal segments according to the state number and using observation symbols appropriate to each segment. At the second stage, the initial values of average and standard deviation were calculated by separating observation symbols into the clusters (FCM or K-means algorithms) that have equal number of states and using observation symbols appropriate to the separated clusters. The implementations of the experimental studies were carried out on three different classification systems such as CHMM, FCM–K-means/CHMM and ANN. These experimental results were obtained for specificity and sensitivity rates 92% and 94% for CHMM, 92% and 97.26% for FCM–K-means/CHMM), respectively. Finally, Sengur et al. investigated the use of principal component analysis (PCA), artificial immune system (AIS) and fuzzy k-NN to determine the normal and abnormal heart valves from the Doppler heart sounds [11]. For reducing the complexity, PCA was used. In the classification stage, AIS and fuzzy k-NN were used. To evaluate the performance of the methodology, a comparative study was realized by using a data set containing 215 samples. The validation of the method was measured by using the sensitivity and specificity parameters; 95.9% sensitivity and 96% specificity rate was obtained. Sengur et al. also investigated the use of Linear Discriminant Analysis (LDA) and Adaptive neuro-fuzzy inference system (ANFIS) for clinical diagnosis and recognition of heart valve disorders [12]. The validation of the method is measured by using the sensitivity and specificity parameters. 95.9% sensitivity and 94% specificity rate was obtained.

2.2. *Feature extraction and construction of the database*

All the original audio DHS signals were acquired from the Acuson Sequoia 512 Model Doppler Ultrasound system in the Cardiology Department of the Firat Medical Centre. DHS signals were sampled at 20 kHz for 5 s (100,000 samples) and signal to noise ratio of 0 dB by using a sound card which has 16-bit A/D conversion resolution and computer software prepared by us in the MATLAB. The Doppler ultrasonic flow transducer used (Model 3V2c) was run in a continuous operating mode 2 MHz. The Doppler signals of the heart valves were obtained by placing the transducer over the chest of the patient with the aid of an ultrasound image. Pre-processing to obtain the feature vector was performed on the digitized signal in the following order [13]:

i. *Filtering*: the stored DHS signals were high-pass filtered to remove unwanted low-frequency components, because the DHS signals are generally in the range of 0.5–10 kHz. A fiftieth-order digital FIR filter with a 500 Hz cut-off frequency along with 51-point symmetric Hamming window was used for this purpose.
ii. *White de-noising*: white noise is a random signal that contains equal amounts of every possible frequency, i.e. its FFT has a flat spectrum [14]. DHS signals were filtered to remove the white noise by using a wavelet packet method. The white de-noising procedure contains three steps [15]:
    1. *Decomposition*: DHS signals were decomposed by using a Daubechies wavelet of order 4 in a wavelet packet manner at 4th level.
    2. *Detail coefficient thresholding*: for each decomposition level, soft thresholding was applied to the detail coefficients.
    3. *Reconstruction*: the filtered signals were reconstructed based on the original approximation coefficients at level 4 and the modified detail coefficients of detail levels.
iii. *Normalization*: DHS signals in this study were normalized using Eq. (1) so that the expected amplitude of the signal is no affected from the rib cage structure of the patient.

$$\mathrm{DHS_{signal}} = \frac{\mathrm{DHS_{signal}}}{\left|(\mathrm{DHS_{signal}})_{max}\right|} \tag{1}$$

The DHS waveform patterns from heart valves are rich in detail and highly non-stationary. After the data pre-processing has been realized, the feature extraction process was carried out. This process has two stages as shown in Fig. 1.

Stage 1 – wavelet packet decomposition: the DHS waveforms decomposed with wavelet packet transform tree decomposition [16]. Daubechies-1 wavelet packet filter ψ was applied to decompose the signals at level 8. So, 256-terminal nodes were obtained at level 8. Each terminal node contains approximately 390 coefficients. The related figure can be seen in Fig. 2.

Stage 2 – entropy calculation: an entropy-based criterion describes information-related properties for an accurate representation of the given signal. Entropy is a common concept in many fields, mainly in signal processing [17]. A method for measuring the entropy appears as an ideal tool for quantifying the ordering of non-stationary signals. The norm entropy was calculated as defined in Eq. (2) of the waveforms at the terminal node signals obtained from wavelet packet decomposition.

$$\underset{j=1}{\overset{256}{E}}(s(j)) = \frac{\sum_{i=1}^{390}\left|s_j(i)\right|^P}{N} \tag{2}$$

where, the entropy E is a vector which contains 256 real numbers, $s_j(i)$ is jth waveform of terminal node signals and i is index of coefficients of terminal node j. In norm entropy, P is the power parameter. During the neural network ensembles learning process, the P and N parameters are updated together with weights to minimize the error and 1.4 and 20 is detected as the optimum value for P and N parameter, respectively. Finally, a feature vector was extracted by computing the 256-entropy values per DHS signal. In other words, 256 features were obtained for each DHS signal.

2.3. *Ensemble-based methods*

The ensemble-based methods create new models by combining the posterior probabilities (for class targets) or the predicted values (for interval targets) from multiple predecessor models. The new model is then used to score new data. Thus, this new model obtains an increase in generalization performance by combining several individual models trained on the same task [18]. A schematic illustration of ensemble model can be seen in Fig. 3.

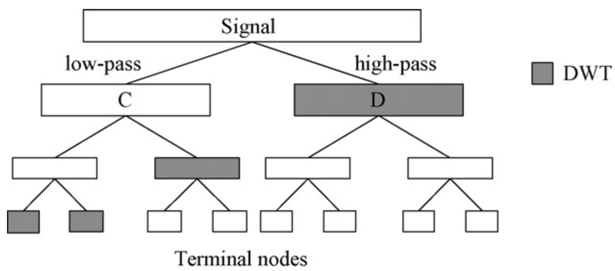

Fig. 2 – Total decomposition tree of a time varying signal using wavelet packet analysis.

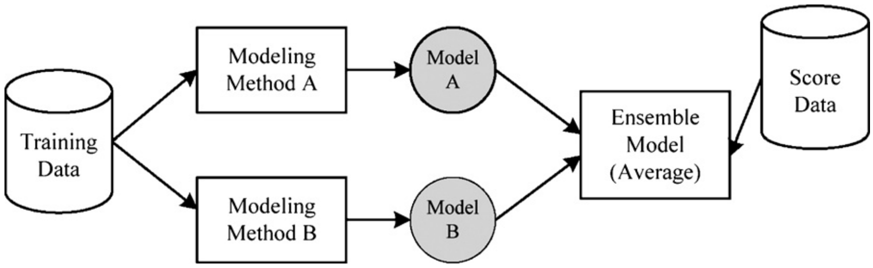

Fig. 3 – A schematic illustration of ensemble model [18].

The creation of an ensemble approach is often divided into two steps: (1) generate individual members, and (2) appropriately combine individual members' outputs to constitute a new output. The basic method for forming ensemble-based methods is to train each member model using random parameters. In the neural network context, these methods include techniques for training with different network topologies, different initial weights, different learning parameters, and learning different portions of the training set [19]. Moreover, methods for creating ensembles focus on creating classifiers that disagree on their decisions. In general terms, these methods alter the training process in an attempt to produce classifiers that will generate different classifications.

3. Proposed methodology and implementation with SAS base software

The proposed methodology, which is illustrated in Fig. 4, is implemented with the SAS Base Software 9.1.3 (License number: 291468). SAS Enterprise Miner streamlines the entire data mining process from data access to model assessment. It supports all necessary tasks within a single, integrated solution while providing the flexibility for efficient collaborations. SAS Enterprise Miner is designed for data miners, marketing analysts, database marketers, risk analysts, fraud investigators, business managers, engineers and scientists who play strategic roles in identifying and solving critical business or research issues [18].

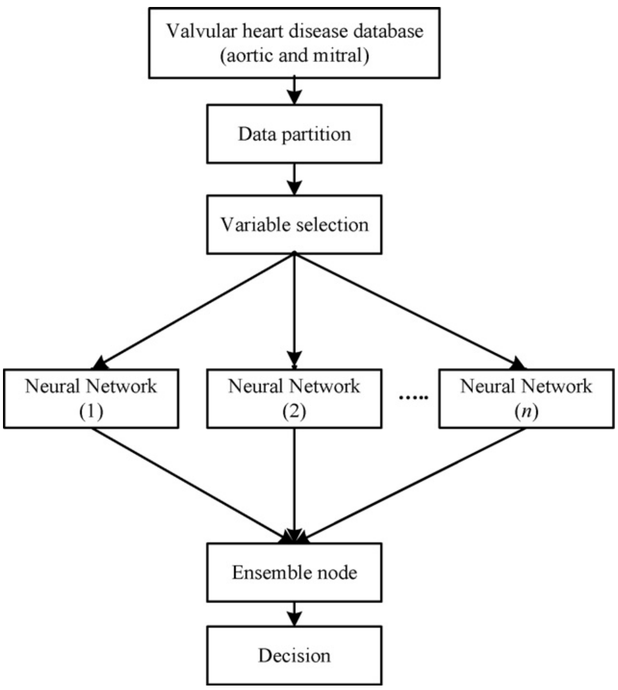

Fig. 4 – The proposed system for heart disease recognition.

SAS Base Software 9.1.3 includes two different programs. These programs are called SAS Enterprise Guide 4.3 and SAS Enterprise Miner 5.2. While SAS Enterprise Guide program 4.3 was used for data pre-processing, SAS Enterprise Miner 5.2 program was used to analyze and recognize the heart disease by combining several neural networks with ensemble node. As can be seen from Fig. 4, the performed system is composed of 6 components. The brief description of each component is given in the following sections.

3.1. *Valvular heart disease database*

This component holds the features that are used to characterize healthy persons and patients. As it was mentioned earlier, the database composed of 257 columns and 215 rows. 1–256 columns indicate the features and 257th column indicates the class labels.

3.2. *Data partition*

Data partition component was used to partition the input data into train and validation data sets. Partitioning provides mutually exclusive data sets. Two or more mutually exclusive data sets share no observations with each other. Partitioning the input data reduces the computation time of preliminary modelling runs.

3.3. *Variable selection*

The purpose of the variable Selection node in Enterprise Miner is to perform a variable selection procedure in determining the best set of input variables for the predictive model from a pool of all possible input variables that best predicts the variability of the unique target variable from the training data set. The Variable Selection node typically performs two steps in selecting the best set of input variables to the predictive model. Initially, the node performs correlation analysis from the sim-

Table 1 – Testing results of the proposed methodology.

	Mitral valve				Aortic valve				All valves			
	Disease	Healthy	Totals	accuracy	Disease	Healthy	Totals	accuracy	Disease	Healthy	Totals	accuracy
Test results (predictions)	TP = 20	FP = 1	21	95.2%	TP = 16	FP = 1	17	94.1%	TP = 36	FP = 2	38	94.7%
	FN = 0	TN = 13	13	100.0%	FN = 0	TN = 18	18	100.0%	FN = 0	TN = 31	31	100%
Totals	20	14	34	97.6%	16	19	35	97.1%	36	33	69	97.4%

ple linear relationship between each input variable and the target variable. From the analysis, the input variables with the highest correlations are retained in the model. However, the shortcoming of this technique is that correlation analysis does not account for the partial correlation between the other input variables in the model. Therefore, inputs could be mistakenly added to or removed from the predictive model. Partial correlation measures the association between each input variable and the target variable in the model, that is, as the values of the input variable change, they will result in the change in values of the target variable in the model, or vice versa. Therefore, this is the reason that the forward stepwise regression procedure is performed in the subsequent step. Stepwise regression takes into account the inter correlation between the input variables in the predictive model. However at times two variables might be uncorrelated with each other unless you take into account a third variable.

3.4. *Neural networks block*

This component was used to classify the feature space. Three independent neural networks models were used to construct this component. There are many types of Neural Networks architectures; however, multi-layer feed-forward neural network is the most widely used for prediction. A multi-layer feed-forward neural network typically has an input layer, an output layer, and one or more hidden layers. In multi-layer feed-forward networks, neurons are arranged in layers and there is a connection among the neurons of other layers. The inputs are applied to the input layer the output layer contributes to the output directly. Other layers between input and output layers are called hidden layers. Inputs are propagated in gradually modified form in the forward direction, finally reaching the output layer. The back-propagation learning algorithm has been used in the feed-forward, single hidden layer neural network. The variants of the algorithm used in the study are the Levenberg–Marquardt (LM), scaled conjugate gradient (SCG) and Pola-Ribiere conjugate gradient (CGP) algorithms. A tangent sigmoid transfer function has been used for both the hidden layer and the output layer. The initial weights were chosen randomly.

3.5. *Ensemble node*

The ensemble node creates new models by combining the posterior probabilities (for class targets) or the predicted values (for interval targets) from multiple predecessor models. The new model is then used to score new data. In Enterprise Miner 5.2, the Ensemble node combines different model outputs. The Enterprise Miner 5.2 Ensemble node does not yet support resampling, bagging, or boosting which are known as common ensemble methods.

The Ensemble node uses the following three different fusion methods to combine results from different modelling nodes. The predicted values, posterior probabilities, and voting posterior probabilities properties can be used to specify the method. In our experiments, we used the Average method.

Average — takes the average of the posterior probabilities (for categorical targets) regardless the target event level, or of the predicted values (for interval targets) from different models as the prediction from the Ensemble node.

Table 2 – Obtained performance parameters with our proposed system and other classifiers from literature.

Method and classifier	Type	No. of patients	Detected as abnormal	Detected as normal	SN = Sensitivity, SP = Specificity
ANN (Turkoglu, 2002)	Abnormal	73	70	3	SN = 95.9%
	Normal	50	3	47	SP = 94%
WPNN (Turkoglu, 2003)	Abnormal	73	69	4	SN = 94.5%
	Normal	50	3	47	SP = 94%
SVM (Comak, 2006)	Abnormal	73	69	4	SN = 94.5%
	Normal	50	5	45	SP = 90%
FCM/CHMM (Uguz, 2006)	Abnormal	73	71	2	SN = 97.3%
	Normal	50	4	46	SP = 92%
LDA, ANFIS (Sengur, 2007)	Abnormal	73	70	3	SN = 95.9%
	Normal	50	3	47	SP = 94%
PCA, AIS and Fuzzy k-NN (Sengur, 2008)	Abnormal	73	70	3	SN = 95.9%
	Normal	50	2	48	SP = 96%
Our proposal, neural networks ensemble	Abnormal	73	71	2	SN = 97.3%
	Normal	50	0	50	SP = 100%

Maximum — takes the maximum of the posterior probabilities (for categorical targets) or of the predicted values (for interval targets) from different models as the prediction from the Ensemble node.

Voting — this method is available for categorical targets only. When you use the voting method to compute the posterior probabilities, two methods are available for voting the posterior probabilities: Average and Proportion.

The Average method for voting posterior probabilities uses the posterior probabilities from the models that predict the same target event. For example, if models M1, M2, M3 predict the event level J1, and model M4 predicts the event level J2, the posterior probability for J1 in the Ensemble node would be computed by averaging the posterior probabilities of J1 from models M1, M2, and M3. Model M4 is ignored.

The Proportion method for voting posterior probabilities ignores the posterior probabilities that are generated from the individual models. Instead, the Proportion method computes the posterior probability for a target value J1 based on the proportion of individual models that predict the same event level. For example, if individual models M1, M2, and M3 predict the target value J1, and model M4 predicts the target value J2, the posterior probability for J1 in the Ensemble node would be 3/4.

4. Experimental classification results

The database contains the aortic and mitral valves of 132 men and 83 women, ages 15 through 80 (mean age = 48 years). A total of 215 valvular classifications were identified, including 56 normal and 54 abnormal aortic valves, and 39 normal and 66 abnormal mitral valves. The classification of abnormal heart valves included both stenosis and insufficiency. A normal valve had no such stenosis or insufficiency.

We realized two different kinds of experiments. Firstly, for calculating the classification accuracy, of the 110 aortic valve patients studied, randomly 70% were selected for training process. Likewise, of the 105 mitral valve patients, again randomly 70% were selected for the training process. The remaining patients were used as the test set. Thus, totally 146 samples were used for training and 69 samples were used for validation. Secondly, for comparing the classification performance of the proposed method with the previous algorithms, of the 110 aortic valve patients, 14 abnormal and 25 normal subjects were selected for the training process. Of the 105 mitral valve patients studied, 33 abnormal and 20 normal subjects were selected for the training process. The remaining patients were used as the test set. The true diagnoses were identified under the supervision of expert physicians using known Doppler and clinical observations.

The classification accuracy of the neural network ensembles model's testing results were given in Table 1. One abnormal heart mitral and aortic valve patterns were classified incorrectly.

The confusion matrix and the calculated sensitivity and specificity rates were given in Table 2. The performance comparison of the proposed system with the other classifiers from literature was also demonstrated in the Table 2. According to these results, higher sensitivity rate (97.3%) was obtained by using the FCM-CHMM and our proposal. But, while FCM-CHMM produced the 92% specificity value, our proposal produced the highest specificity rate (100%). SVM method gained the worst specificity rate (90%). While ANN, WPNN and LDA-ANFIS methods obtained the same 94% specificity rate, ANN, LDA-ANFIS and PCA-AIS and fuzzy k-NN produced the same sensitivity rate (95.9%). And finally the SVM and WPNN produced the lower sensitivity rate (94.5%).

5. Conclusion and discussion

Up to now, several studies have been reported focusing on valvular heart disease diagnosis [7–13]. These studies applied different methods to the given problem and achieved high classification accuracies. In this study, SAS Enterprise Miner 5.2 was used to construct a neural networks ensemble-based methodology for diagnosing of the valvular heart disease. Experiments were conducted on the valvular heart disease dataset to diagnose heart disease in a fully automatic manner. Three independent neural networks models were used to construct the ensemble model. The number of neural networks node in the ensemble model was also increased but no performance improvement was obtained. The experimental results gained 97.4% classification accuracy, 100% sensitivity and 96% specificity values. To the best of our knowledge, this classification accuracy is the highest so far.

SAS Enterprise Miner 5.2 supports all necessary tasks within a single, integrated solution while providing the flexibility for efficient collaborations. It also gives opportunities to the user to deal with various performance evaluation test methods. This allows the user to evaluate their system performance from many different points of views. Thus, SAS base software can be used in many machine intelligence applications.

Conflict of interest

None.

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REFERENCES

[1] http://yourtotalhealth.ivillage.com/heart-disease-fast-facts.html (accessed 13.02.08).
[2] http://www.americanheart.org (accessed 13.02.08).
[3] P.I.J. Keeton, F.S. Schlindwein, Application of Wavelets in Doppler Ultrasound, vol. 17, number 1, MCB University Press, 1997, pp. 38–45.
[4] I.A. Wright, N.A.J. Gough, F. Rakebrandt, M. Wahab, J.P. Woodcock, Neural network analysis of Doppler ultrasound blood flow signals: a pilot study, Ultrasound in Medicine & Biology 23 (5) (1997) 683–690.
[5] B.C.B. Chan, F.H.Y. Chan, F.K. Lam, P.W. Lui, P.W.F. Poon, Fast detection of venous air embolism is Doppler heart sound using the wavelet transform, IEEE Transactions on Biomedical Engineering 44 (4) (1997) 237–245.
[6] I. Guler, M.K. Kiymik, S. Kara, M.E. Yuksel, Application of autoregressive analysis to 20 MHz pulsed Doppler data in real time, International Journal Biomedical Computing 31 (3–4) (1992) 247–256.
[7] I. Turkoglu, A. Arslan, E. Ilkay, An expert system for diagnosis of the heart valve diseases, Expert Systems with Applications 23 (2002) 229–236.
[8] I. Turkoglu, A. Arslan, E. Ilkay, An intelligent system for diagnosis of heart valve diseases with wavelet packet neural networks, Computer in Biology and Medicine 33 (4) (2003) 319–331.
[9] E. Çomak, A. Arslan, I. Turkoglu, A decision support system based on support vector machines for diagnosis of the heart valve diseases, Computers in Biology and Medicine 37 (2007) 21–27.
[10] H. Uguz, A. Arslan, I. Turkoglu, A biomedical system based on hidden Markov model for diagnosis of the heart valve diseases, Pattern Recognition Letters 28 (4) (2007) 395–404.
[11] A. Sengur, An expert system based on principal component analysis, artificial immune system and fuzzy *k*-NN for diagnosis of valvular heart diseases, Computers in Biology and Medicine 38 (3) (2008) 329–338.
[12] A. Sengur, An expert system based on linear discriminant analysis and adaptive neuro-fuzzy inference system to diagnosis heart valve diseases, Expert Systems with Applications 35 (1–2) (2008) 214–222.
[13] A. Sengur, I. Turkoglu, A hybrid method based on artificial immune system and fuzzy k-NN algorithm for diagnosis of heart valve diseases, Expert Systems with Applications 35 (3) (2008) 1011–1020.
[14] S.R. Devasahayam, Signals and Systems in Biomedical Engineering, Kluwer Academic Publishers, 2000.
[15] A. Bakhtazad, A. Palazoglu, J.A. Romagnoli, Process data de-noising using wavelet transform, Intelligent Data Analysis 3 (October) (1999) 267–285.
[16] A. Sengur, I. Turkoglu, M.C. Ince, Wavelet packet neural networks for texture classification, Expert Systems with Applications 32 (March (2)) (2007).
[17] R.Q. Quiroga, O.A. Roso, E. Basar, Wavelet entropy: a measure of order in evoked potentials., Elsevier Science, Evoked Potentials and Magnetic Fields, September 49 (1999) 298–302.
[18] http://support.sas.com/documentation/ (accessed 20.01.08).
[19] R. Das, I. Turkoglu, A. Sengur, Effective diagnosis of heart disease through neural networks ensembles, Expert Systems with Applications (2008); doi:10.1016/j.eswa.2008.09.013.