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RESEARCH ARTICLE

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Microscopic abnormality classification of cardiac murmurs using ANFIS and HMM

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Abstract
Auscultation of heart dispenses identification of the cardiac valves. An electronic stethoscope is used for the acquisition of heart murmurs that is further classified into normal or abnormal murmurs. The process of heart sound segmentation involves discrete wavelet transform to obtain individual components of the heart signal and its separation into systole and diastole intervals. This research presents a novel scheme to develop a semi-automatic cardiac valve disorder diagnosis system. Accordingly, features are extracted using wavelet transform and spectral analysis of input signals. The proposed classification scheme is the fusion of adaptive-neuro fuzzy inference system (ANFIS) and HMM. Both classifiers are trained using the extracted features to correctly identify normal and abnormal heart murmurs. Experimental results thus achieved exhibit that proposed system furnishes promising classification accuracy with excellent specificity and sensitivity. However, the proposed system has fewer classification errors, fewer computations, and lower dimensional feature set to build an intelligent system for detection and classification of heart murmurs.

KEYWORDS
cardiac murmurs, fuzzy inference system, quantitative morphology, wavelet transform

1 | INTRODUCTION

We are living in a world where technological advancements are taking place at a high speed that day by day we have more accurate, effective, and easy-to-operate equipment (Iqbal, Khan, Saba, & Rehman, 2017; Jamal, Alkawaz, Rehman, & Saba, 2017). The usage of traditional techniques is reduced by the application of digital and integrated electronics in the design of equipment related to biomedical signal processing (Abbas et al., 2016). In the current age, the luxurious lifestyle and unhygienic food resulting in an increasing number of heart patients due to which the demand for economical and effective medical facilities has been increased (Husham, Alkawaz, Saba, Rehman, & Alghamdi, 2016; Iftikhar, Fatima, Rehman, Almazyad, & Saba, 2017). Listening with a stethoscope is an effective technique to diagnose a number of heart valve disorders but it requires a skilled and experienced physician to detect the abnormalities and interpret them. Auscultation based methods are also not feasible in telemonitoring cardiac sound systems that require well-trained doctors for analysis of heart sounds. Phonocardiography (PCG) provides a quantitative analysis of the graphical record of the heart sounds with a traditional or modern sound sensor placed on a specific location on the chest. PCG signals contain useful information to reflect the normal function of the heart. Murmurs are unusual heart sounds that are heard in a cardiac cycle due to any disorder in the structure of heart valves. Heart murmurs are regarded as one of the important indicators for diagnosis of heart valve disorder due to a certain type of heart disease (Amiri, Movahedi, & Kazemi, 2017; Song, Liu, Liao, & Li, 2014; Tejman-Yarden, Levi, & Beizerov, 2016). Cardiovascular diseases (in various forms) are one of the major cause of a significant number of deaths and disabilities (Becerra, Orrego, & Trejos, 2013). Nowadays, in most of the hospitals, electrocardiography (ECG), echocardiography and PCG are the common methods that used for diagnosis of heart diseases (Jamal et al., 2017; Mughal, Muhammad, Sharif, Saba, & Rehman, 2017). ECG exhibits heartbeat, rhythm and erythematic but it does not classify murmurs. Conversely, PCG and echocardiography explain whether the abnormality is due to murmurs, muscles, veins or valves and so forth, but echocardiography is costly technique and it also does not yield better quality images for bulky (overweight) persons or patients suffering from lung diseases (Ahmed, Dey, & Ashour, 2017; Garde, Sörnmo, & Laguna, 2017; Zhong, Wan, Huang, Cao, & Xiao, 2013). To overcome these limitations, a computer-aided cognitive system could be developed to assist the cardiologists for heart murmur detection at early stages and differentiate the normal heart sounds from the sounds with certain pathological indications (Norouzi et al., 2014; Saba, Al-Zahrani, & Rehman, 2012).

Heart sounds are produced due to turbulent flow of blood at the closure of heart valves. S1 (the first heart sound) and S2 (the second heart sound) are two prominent components present in the cardiac sound cycle. S1 occurs at beginning of systole and it is produced due to the closure of mitral and tricuspid valves. S2 originates at the end of systole by the closing of aortic and pulmonary valves. Some other sound components like a thrill, gallop rhythms (S3, S4) and heart murmurs may also exist in the heart sound. S3 (the third heart sound) produces as a result of vibration of blood backwards and forward inside walls of the ventricles by inrushing of blood from the atria. S4 (the fourth heart sound) occurs at the contraction of atria and it is produced due to inrushing of blood into both ventricles. S3 and S4 could occur in both healthy persons and patients suffering from pathological murmurs. Murmurs are extra or unusual heart sounds that coexist with normal heart sounds. Murmurs have a high frequency as compared to the healthy heart sounds, ranging from faint to loud (Saba, 2017). Murmurs could be classified into different categories depending on their location of occurrence. Most common artefacts in the cardiovascular system are valvular stenosis and regurgitation. When leaflets of a heart valve adhere together due to some tissue and therefore blood cannot flow through the valve satisfactorily, termed as stenosis of valves. When valves edges are damaged enough by some tissue that allows the backflow of blood to atria during ventricular systole, this is known as regurgitation of the valve. Regurgitation co-exists with stenosis (Rahim, Norouzi, Rehman, & Saba, 2017a, 2017b).

Several studies were performed to propose an intelligent system for heart murmurs classification in the past (Chen, Yao, & Chen, 2016). Patidar and Pachori (2014) tunable-Q wavelet transform was used for segmentation of heart sound into individual components. The features extracted using Fourier-Bessel expansion to feed the LS-SVM classifier with RBF kernel function to distinguish the normal sound and murmurs. This method possesses less computation complexity due to effective features, but no significant classification accuracy was observed in aortic regurgitation and mitral regurgitation. S1 duration, S2 duration, heartbeat rate, and S1 to S2 intensity ratio were used as features in a fuzzy neural network with structure learning for classification of murmurs (Song et al., 2014). Amiri and Armano (2013) proposed screening of murmurs in newborns and employed wavelet transform and k-means clustering. The feature set contained Wigner bispectrum, Bispectrum, and Shannon energy is used to differentiate innocent and pathological murmurs. The approach of murmur classification proposed by Becerra et al. (2013) presents a hybrid technique that uses empirical mode decomposition and Hilbert-Huang Transform. It is applied to different intrinsic mode functions. Hidden Markov Model (HMM) based heart murmur recognition was employed with Mel-frequency cepstral coefficients (MFCC) for feature extraction but for murmurs having large energy values may affect the classification accuracy. A variety of other features including murmur likelihood as temporal feature and HMM state likelihood followed by support vector machine (SVM) is proposed by Kwak and Kwon (2012). Artificial neural network (ANN) based recognition of the cardiac valve disorder has been performed using systole frequency and diastole frequency as features (Gutierrez, Flores, & Strunic, 2012). The entropy of wavelet coefficients is a useful feature for the comparative study of different classifiers (Safara, Doraisamy, Azman, Jantan, & Ranga, 2012). Zhang et al. (2012) proposed singular value decomposition based classification using Hankel matrix to differentiate normal heart sounds and murmurs. Discrete wavelet transform (DWT) was used for segmentation and Shannon entropy as a feature in adaptive-neuro fuzzy inference system (ANFIS) based classifier (Uguz, 2012). This technique is silent for classification accuracy of murmurs other than mitral and pulmonary stenosis. A set of features extracted from wavelet coefficient matrix by QR decomposition and the classification algorithm of the CART are used in murmur classification (Chen, Wang, Shen, & Choy, 2012). Heart murmurs detection method proposed by Garcia, Vargas, and Dominguez (2011), presents complexity analysis with regulatory features including fuzzy entropy, sample entropy, approximate entropy, and Gaussian kernel approximate entropy with k-nearest neighbor (KNN) and SVM. A comparison among Fuzzy rule-based classifiers is presented by Anushya and Pethalakshmi (2011) using the correct rate of recognition of murmurs. The classes of murmurs are not specified in this study. Kao and Wei (2011) uses coefficients of short-time Fourier transform and SVM to distinguish normal PCG signals and murmurs. Wu, Kim, and Bae (2010) differentiate innocent murmurs and various abnormal heart sounds describe HMM as a classifier with MFCC features. Time-frequency representation of segmented heart samples using a homomorphic filter is proposed by Gupta, Palaniappan, Swaminathan, and Krishnan (2007) for murmur recognition by neural network classifier. The features set comprising on systole energy, diastole energy, spectral coefficients and cepstral coefficients are used for recognition of PCG signals as normal and murmurs (systolic and diastolic) category. Vepa (2009) classified heart murmurs by using SVM, multi-layer perceptron, and KNN as classifiers. Additional, related work on murmur classification could be studied in the literature (Avci & Turkoglu, 2009; Chauhan, Wang, Lim, & Anantharaman, 2008; Chung, 2006, 2007; Rad, Rahim, Rehman, & Saba, 2016; Ricke, Povinelli, & Johnson, 2005).

The organization of the remaining paper is as such, section 2 presents research methodology, section 3 exhibits results, section 4 focus and analysis, discussion and finally, the conclusion is drawn in section 5.

2 | PROPOSED METHODOLOGY

The schematic diagram of the proposed murmur classification system is exhibited in Figure 1.

2.1 | Dataset generation

The dataset used in this work comprises of 150 normal heart sounds and 80 abnormal heart sounds. The abnormal PCG sound signals

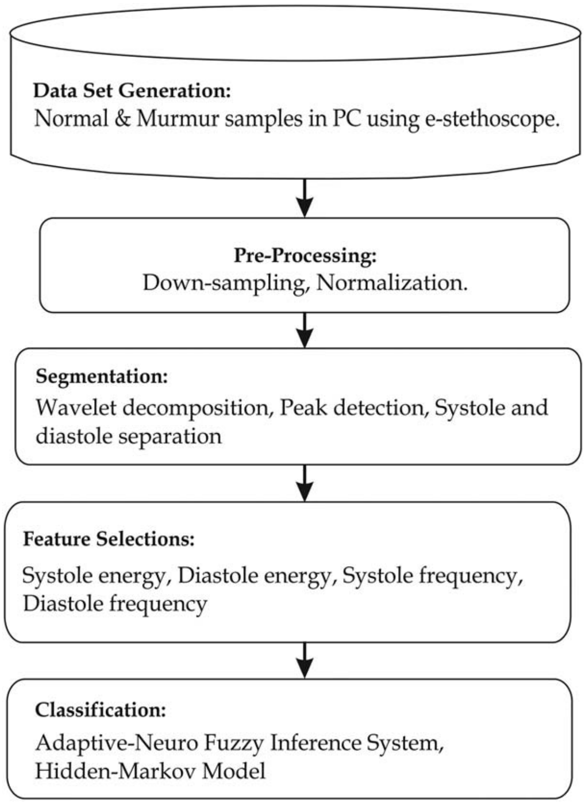

FIGURE 1 Architecture of proposed system for murmurs classification

contain three types of murmurs including mitral stenosis (MS), aortic regurgitation (AR), and mitral regurgitation (MR). PCG signals are attained by using an electronic stethoscope (Littmann® 3200). This stethoscope has 85% ambient noise reduction. All research ethics adopted and this study is approved by Research Ethics Committee (IREB) AMC, Pakistan. Following validation of this data by a cardiologist, PCG samples are recorded in the personal computer as . *wav* format using Bluetooth® technology of e-stethoscope.

2.2 | Preprocessing

In the first step of preprocessing, PCG signals are de-noised by applying a high-pass Chebyshev Type-I filter with cut-off frequency of 40 Hz to remove stethoscope movement sounds. In next step, down-sampling of the PCG signals by a factor four is performed so that the details and approximate coefficients obtained in the wavelet analysis result in such frequency bands containing the maximum power of S1 and S2.

Normal heart sounds have low-frequency contents. Conversely, heart murmurs (abnormal heart sounds) contain high-frequency components but having less frequency as that of ambient noise and human speech signals. Following noise removal, PCG signals are normalized by (1) to set the variance of the signal within the limit of [−1, 1].

$$x_1 = \frac{x_d}{\max(|x_d|)} \tag{1}$$

where x_d is PCG signal after down-sampling & x_1 is a normalized signal.

2.3 | Segmentation of PCG signals

After preprocessing, heart sound signals were segmented into their individual components. The segmentation process is exhibited in Figure 2 and Figure 3.

Discrete Wavelet Transform is a useful tool for analyzing the non-stationary signals or signals with transient phenomena of interest (Trejo, Manrique, Liorente, Velasco, & Dominguez, 2009). It allows the user to analyze each component of the signal by decomposing it into its parts belong to different frequency regions. Wavelet transform has the property to form the mother wavelet function that is supportive to extract valuable and appropriate information about the signal under observation (Uguz, 2012).The flexibility in resolution has earned DWT the reputation for being useful in exploring nonstationary signals with

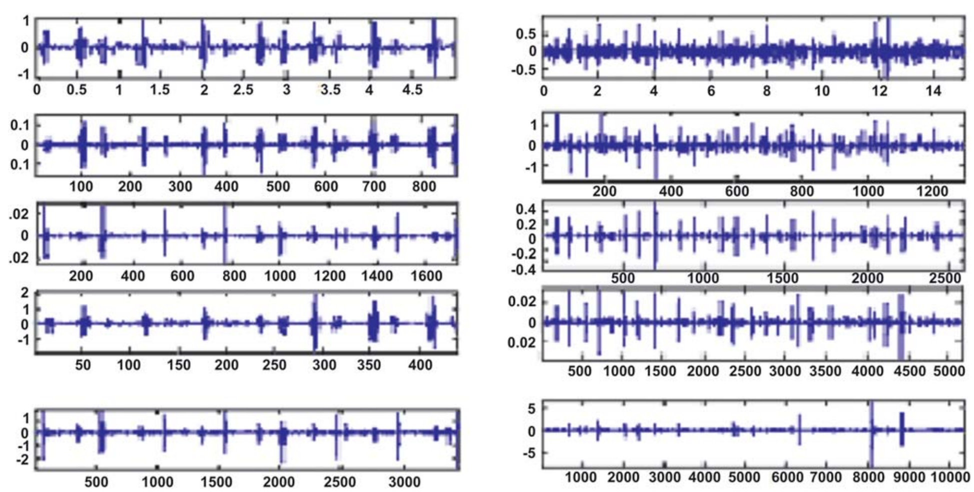

FIGURE 2 Wavelet Db-6 detailed coefficients of normal PCG vs mitral regurgitation (a) original heart sound, (b) 5th level detail coefficients, (c) 4th level detail coefficients, (d) 3rd level detail coefficients, (e) 2nd level detail coefficients, where *x*-axis is number of samples and *y*-axis is amplitude [Color figure can be viewed at wileyonlinelibrary.com]

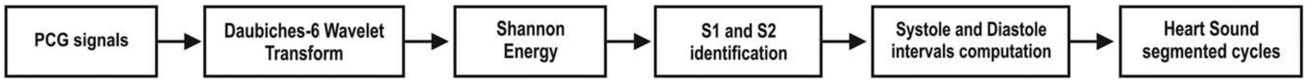

FIGURE 3 Phonocardiogram PCG segmentation process

sudden transients (Kumar et al., 2006) The usefulness of wavelet in the segmentation process is that at higher frequencies it uses a short length of data windows (Bai & Lu, 2005) and contrary to it, at lower frequencies it uses a larger length of data windows. In proposed research, Daubechies-6 DWT is selected, since it has dynamic scales and positions. Due to this feature, less number of coefficients with better frequency-scale variation over time is attained. Its shape is designed in such a way that it is capable of taking into account the transient nature of the sounds. It facilitates the separation of two prominent heart sounds (S1 and S2) in normal heart signal which is generally lie in low-frequency range (Paul, Wan, & Nelson, 2006). Wavelets have better resolution in time and frequency that is why they give precise information in both domains and they are preferable to use in PCG signal analysis (Gupta et al., 2007). Signal decomposition by Wavelet analysis involves a series of high-pass filters (HPF) and low-pass filters (LPF) (Vepa, 2009).

In wavelet decomposition algorithm, the input PCG signal is separated into two parts. One of them is called "detailed signals or detailed coefficients" and these are high-frequency components. The second part of the signal is called "approximations or profile signals" and they are low-frequency components. Frequency contents (both low frequency and high frequency) of the input signals is extracted by using multi-stage wavelet decomposition. The 5th level detailed coefficients are computed by successive processing of scaling and wavelet

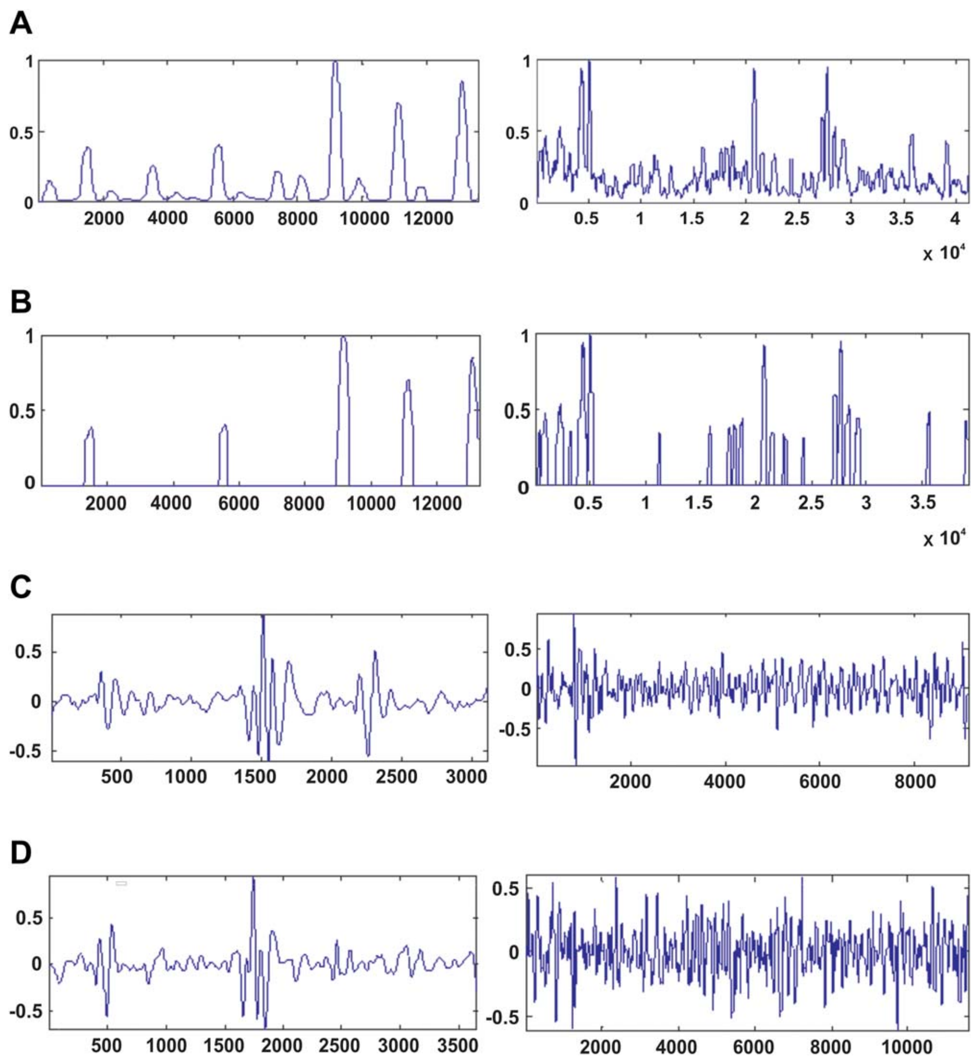

FIGURE 4 Segmentation results for PCG signals for class of (1) normal heart sounds (2) mitral regurgitation: (a) normalized average Shannon energy, (b) detection of peaks, (c) segment of systole interval, (d) segment of diastole interval, where *x*-axis is number of samples and *y*-axis is amplitude (unit-less converted) [Color figure can be viewed at wileyonlinelibrary.com]

functions. 5th level detailed coefficients play an important part in supplementary processing. Results are exhibited in Figure 4.

The successive filter operation is performed by following equations:

$$y=\sum_{k=-\infty}^{\infty} x_d[k]h[n-k] \tag{2}$$

where x_d is PCG signal, h is impulse response of the applied filter.

The output of HPF and LPF can be described as:

$$Z=\sum_{n=0}^{1} x_d[n]\ h[2k-n] \tag{3}$$

$$Y=\sum_{n=0}^{1} x_d[n]\ h[2k-n] \tag{4}$$

Where Z represents the output of HPF, Y represents the output of LPF, n is number of samples and h is impulse response of applied filter.

These filters relate to the wavelet function in such a way that the down-sampled output corresponds to the filtering of the signal with the wavelet function at a particular scale. The input signal to wavelet was first down-sampled by a factor four so that the details and approximate coefficients obtained in the wavelet analysis result in such frequency bands containing the maximum power of S1 and S2.

In the second step of segmentation, Shannon Energy of the reconstructed wavelet signal is computed by (5). Shannon energy boosts the frequencies in that portion of the signal where S1 and S2 lobes are present. Another feature of using Shannon energy is that it eliminates the low-valued noisy portion from PCG signals that makes the envelope less noisy and easily readable. The envelope of the signal is extracted by zero-crossings of normalized average Shannon energy. In next step, sound lobes are highlighted using peak detection. In this step, a threshold level to extract the high-intensity sound lobes is derived by excluding the noise effect and the part of the signal having very low-intensity. There exist more than one peak above the threshold level but only one peak for each overshoot is selected. The selection criteria of the peak for every overshoot is selection of one peak. However, if there are more than two peaks it shows that there is a splitting of the first or second heart sound. In this case, the first peak is selected so as to obtain the onset of each sound.

Following, detection of peaks of the input signal, S1 and S2 were identified using relative position of the sound lobes by computing the lobe boundaries. Grouping mechanism is applied to both of the intervals to form the sound lobes. Sound lobe with a larger time interval (S2 to S1) detected as diastole and the second one with a smaller time interval (S1 to S2) as systole. These steps are repeated for all the acquired normal and abnormal heart sounds to obtain heart sound cycles.

$$S.E=-\frac{1}{N}\sum_{n=1}^{N} x_r^2(n).\log x_r^2(n) \tag{5}$$

where, x_r is the PCG signal obtained after 5th level reconstruction in wavelet analysis and N is the number of samples in the particular window.

2.4 | Feature extraction

Feature extraction is a process of reducing the volume of the data because the techniques used in classification should have an optimal number of features (Becerra et al., 2013). In our work, it is not the wise decision to process the PCG signals in any analysis algorithm in a direct manner without extracting useful features. Consequently, there is need to transform the data into a useful representation to extract the features that are suitable enough to train the classifier for effective murmur recognition. The application domain based knowledge is also important to obtain the best features to achieve good classification results. The raw set of features in both time-domain and frequency domain are computed, given in Table 1. Short-term windowing technique in time domain analysis of PCG signals is applied. In proposed methodology, the signal obtained after 5th level decomposition is first divided into short-term frames or windows. All PCG segments are broken into overlapping frames to compute a set of features per frame. This type of processing generates a sequence of feature vectors per PCG signal. In time-domain, Shannon entropy, systole energy, diastole energy, and zero–crossing rate features are extracted. Based on spectral analysis of PCG signals, spectral entropy, systole frequency, diastole frequency and spectral centroid are calculated as features in frequency-domain.

TABLE 1 List of extracted set of features

Features	Description/expressions
Shannon entropy	$H=-\sum_{k=1}^{N}(e_k.\log e_k)$
Systole energy	$E_S=\max(E_{S1}, E_{S2}, E_{S3})$
Diastole energy	$E_D=\max(E_{D1}, E_{D2}, E_{D3})$
Zero-crossing rate	$Z=\frac{1}{2w}\sum_{m=1}^{w}\lvert \mathrm{sgn}\ [x(m)]-\mathrm{sgn}\,[x(m-1)]\rvert$
Spectral entropy	$H=-\sum_{f=0}^{K-1} n_f\ \log(n_f)$
Systole frequency	$f_S=\frac{(f_1 * E_{S1})+(f_2 * E_{S2})+(f_3 * E_{S3})}{E_{S1}+E_{S2}+E_{S3}}$
Diastole frequency	$f_D=\frac{(f_1 * E_{D1})+(f_2 * E_{D2})+(f_3 * E_{D3})}{E_{D1}+E_{D2}+E_{D3}}$
Spectral centroid	$C_i=\frac{\sum_{m=1}^{w} m\ X_i(m)}{\sum_{m=1}^{w} X_i(m)}$

In MATLAB, a low-pass and band-pass filters is designed. The first low-pass filter is Chebyshev Type-I finite impulse response (FIR) filters with cut-off frequency of 200 Hz. The second is band-pass FIR filter having a frequency band of 250–400 Hz. The third filter is also a band-pass FIR filter (relatively HPF as compared to second BPF) with the frequency band of 150–1000 Hz. The characteristic of this filtering process is that the output sequence has no group delay because of having zero-phase distortion. The cutoff frequencies of these filters are f_1, f_2, and f_3 respectively and they are selected in relation to the frequency ranges of a normal heart sound, and pathological murmurs. The systole segments obtained in segmentation process were passed through these filters to obtain systole energy values E_{S1}, E_{S2}, and E_{S3} corresponding to each filter. Similarly, after passing diastole segments through the first, second and third filter we get diastole energy values E_{D1}, E_{D2}, and E_{D3} respectively. In next step, the maximum value of these energies is chosen to select systole energy (E_S) and diastole energy (E_D) as features that are used in classification. The rest of the features were calculated according to the expressions given in Table 1.

However, in feature extraction process, some redundant features and some excessive number of high-dimensional feature vectors are also observed. The selection of a final set of features is adaptive because the elements of selected feature set depend on classification accuracy during the training phase of classifiers. The feature selection procedure iteratively searches and adds the features to form the final feature set in classifier training to obtain better classification accuracy.

2.5 | Classification

Classification is the main contribution of the current research. The classification process has two main phases: one is to train the classifier and the second is testing the data after training. The whole data is divided into two categories such that 70% for the training purpose and 30% for the testing. An iterative procedure is adopted to tune the parameters of different classifiers to train these classifiers (Saba, Rehman, & Elarbi-Boudihir, 2014; Rehman, & Saba, 2014). The parameter selection of a specific classifier in training phase relies on the complexity of the assignment. Finally, classification systems is the fusion of ANFIS and HMM. Both classifiers are trained and tested on the same set of features and their classification accuracy was computed.

2.5.1 | Adaptive-neuro fuzzy inference system

ANFIS is the conjunction of fuzzy inference system and ANNs. ANFIS based models are commonly used in a variety of biomedical engineering problems (Uguz, 2012)

In the proposed research, Mamdani's inference system based ANFIS classifier is employed and it uses rule-based (IF-Then rules). The training parameters of this classification system have been given in Table 5.

In the first step, the feature set containing systole energy, systole frequency, diastole energy and diastole frequency was given as input to the fuzzy inference system. The calculated numeric values of these features (crisp values) were converted into input linguistic variables and membership ranges (low, medium, high) were assigned to each input linguistic variable. In the second step, rules formed in rule-based were applied on the antecedent part to assign weights (rule strength) to input variables. In next step, implications were performed on consequent part i.e. rules were evaluated in a parallel fashion using fuzzy reasoning. In the fourth step, the outputs of each rule were combined into a single fuzzy set for every output membership function in three linguistic regions.

In the fifth step, each output linguistic variable was converted into single crisp value by defuzzification process. Centroid calculation method is adopted for this purpose using equation 8:

$$z=\frac{\sum_{k=1}^{t} Z_k \cdot \mu_c\ (Z_k)}{\sum_{k=1}^{t} \mu_c\ (Z_k)} \tag{8}$$

where z is the centroid (centre of gravity), μ_c represents the probability of class c of the output variable at Z_k.

2.5.2 | Classification system using HMM

Hidden Markov model is considered to be a stochastic model or a variant of a finite state machine that is based on Markov chains. The methodology based on HMM is widely used in pattern recognition and speech processing for temporal representation of signals. HMM-based models have the property of controlling the transition likelihood between the states and the selection of states as well. The accuracy rate of classification systems based on HMM is greatly depended on the correct selection of HMM parameters. Therefore, in many applications, an iterative procedure of HMM parameters optimization has been adopted after initial assignments of HMM parameters. In compact form, HMM is represented as $\lambda = (M,\ \pi,\ A,\ B)$ and the parameters define a complete HMM are given below:

π = Initial distribution of states

N = Number of states

M = The number of distinct observations, $O = \{O_1, O_2, \ldots, O_M\}$

$A = a_{ij} = P[q_t = S_j\ q_{t+1} = S_i]$, The state transition probability distribution, indicates probability of state change from state S_i to S_j

$B = \{b_j\ (k)\}$ = The probability distribution of the observations

Left-to-right HMM model approach for classification of PCG signals is applied in proposed research work. The extracted features of heart sound data were considered as observation sequences of each HMM. Four HMMs were formed and each type of model was trained for a particular type of heart sound including normal, MS, MR, and AR. In observation training phase, an iterative approach was used for optimization of model parameters and for each model, the value of parameter π set at unity because PCG signals are time-variant series in one dimension. In the next step, forward-backwards recursive procedure of Baum-Welch re-estimation approach is implemented that estimates the model parameters by maximum likelihood computation. Forward probability is calculated by using the following equation:

$$\alpha_{t+1}(j)=\left[\sum_{i=1}^{N} \alpha_t(i) a_{ij}\right] b_j\ (O_{t+1}) \tag{9}$$

where, $1 \le t \le T-1$, $\alpha_t\ (i)$ is the probability of the event that observations $O_1, O_2 \ldots O_t$ are observed and S_j state is approached at $t+1$ after S_i state at time t. The iterative backward probability is calculated by given equation:

$$\beta_t(i)=\sum_{j=1}^{N} a_{ij} b_j\ (O_{t+1})\ \beta_{t+1}(j) \tag{10}$$

where, $t = T-1, T-2, \ldots, 1$; $1 \le j \le N$, $\beta_t(i)$ is called "backward variable." It defines observation sequence probability for S_i state at time t (within range of $t+1$ to end).

For each class of PCG signals, $P\ (O|\lambda_i)$ $(i = 1, \ldots, 4)$ estimated by a separate HMM and used Bayes' rule to classify the heart sounds in normal and murmurs (MS,MR,AR) category.

TABLE 2 Classification confusion matrix for ANFIS

	Normal	MS	MR	AR
Normal	148	1		1
MS		24	1	
MR	1		29	
AR		1		24

3 | EXPERIMENTAL RESULTS

This research proposed a novel scheme to develop a cognitive cardiac valve disorder diagnosis system. Fused classification systems based on adaptive neuro-fuzzy inference system (ANFIS) and HMM is applied. Both classifiers were trained using the selected features to correctly identify normal and abnormal heart sounds. An electronic stethoscope is used for the acquisition of normal and murmurs heart sounds.

In ANFIS classification system, training is performed for each type of heart sound signal PCG i.e. samples were fed to the classifier for a specific class with extracted set of features. In next step, the testing phase of the classifier was reached and the results of this testing process are listed in Table 2 in the form of the confusion matrix. Table 2 indicates that two healthy cardiac sound signals are falsely classified as MS and AR class, one sample of MS falls in MR class, one sample of MR class as normal and one sample of AR in MS class.

In classification system using HMM, we trained four models for each of the output class of murmur and normal PCG signal.

Following iterative procedure of parameter optimization of these models, classification results obtained that are recorded in confusion matrix in Table 3. This matrix shows that all the subjects with normal heart sound are correctly classified while one subject is incorrectly classified as MR that originally belongs to MS and two subjects of MR are prone to be false classification as MS and normal heart signal. Moreover, two subjects of AR are falsely classified in MS class.

$$\text{Sensitivity} = \left[\frac{TP}{TP+FN}\right] \times 100 \quad (11)$$

$$\text{Specificity} = \left[\frac{TN}{FP+TN}\right] \times 100 \quad (12)$$

$$\text{PPV} = \left[\frac{TP}{TP+FP}\right] \times 100 \quad (13)$$

$$\text{NPV} = \left[\frac{TN}{TN+FN}\right] \times 100 \quad (14)$$

where TP, FN, TN, FP, PPV, and NPV represent true positive, false negative, true negative, false positive, positive predictive value, and negative predictive value respectively.

TABLE 3 Classification confusion matrix for HMM

	Normal	MS	MR	AR
Normal	150			
MS		24	1	
MR	1	1	28	
AR		2		23

TABLE 4 Statistical parameters results of proposed methods: ANFIS and HMM, in classification of heart murmurs

Classification method	Type of PCG signal	Sensitivity (%)	Specificity (%)	Positive predictive value (%)	Negative predictive value (%)
ANFIS	Normal	98.75	98.67	97.53	99.33
	MS	96	99.02	92.31	99.51
	MR	96.67	99.50	96.67	99.50
	AR	96	99.51	96.00	99.51
HMM	Normal	100	99.33	98.77	100.00
	MS	96	98.54	88.89	99.51
	MR	93.33	99.50	96.55	99.00
	AR	92	100	100.00	99.03

4 | ANALYSIS AND DISCUSSION

Classification performance of the proposed system is evaluated by computing statistical parameters: sensitivity, specificity, positive predictive value, and negative predictive value for each of the murmur class. Sensitivity is the probability of correctly detecting a signal with a murmur (original class of signal) whereas specificity is the probability of correctly excluding a normal PCG signal in classification.

The positive predictive value is the measure of the likelihood that someone has the specific characteristic if the test is positive. The negative predictive value foresees how likely someone is not to have the characteristic. These statistical values are very important to calculate particular disorder how useful the test is to detect a particular disorder in the given population. The results of this statistical analysis are given in Table 4.

A comparison of the proposed classification system with state of the art classification methods is presented in Table 6. According to the statistics given in this table, the proposed classification methods proved efficient in classification performance as compared to most of the reported research on given set of features.

In proposed classification system using systole energy, systole frequency, diastole energy, and diastole frequency as features followed by HMM, classification accuracy of 98.7% of heart murmurs is achieved.

TABLE 5 ANFIS parameters for classification

Parameter description	Setting
FIS type	Mamdani
Number of Inputs	4
Number of Outputs	4
Input membership function type	Trapezoidal, Triangular
Output membership function type	Trapezoidal, Triangular
Number of rules	81
Defuzzification method	Centroid
Number of layers	5

TABLE 6 Classification accuracy comparison of proposed methods with some of the existing literature

Classification Approach	Accuracy (%)
SVD/Shannon entropy/Regression Trees (Zhang et al., 2102)	90.0
Tunable Q Wavelet/Kurtosis-Skewness/SVM (Becerra et al., 2013)	94.1
Morlet Wavelet/MFCC/Hidden Markov model (Zhong et al., 2013)	94.5
Discrete Wavelet/Cepstral features/SVM (Vepa, 2009)	95.2
Cepstral features/HMM State likelihood-SVM (Kwak and Kwon, 2012)	97.5
Wavelet/Shannon energy/Spectral features/ANFIS (Proposed method)	97.9
Wavelet/Shannon energy/Spectral features/HMM (Proposed method)	98.7

5 | CONCLUSION AND FUTURE WORK

This article has presented a novel fusion approach for an intelligent heart murmurs classification system. PCG signals acquired from subject persons with healthy and murmurs including mitral stenosis, mitral regurgitation, and aortic regurgitation. DWT was used for decomposition of heart sound into its individual components for separation of heart sound into systole and diastole intervals. The current work includes extraction of features using Shannon energy and peak conditioning during segmentation of heart sound signals. Following an iterative procedure, features set containing systole energy, diastole energy, systole frequency and diastole frequency was selected. These features were fed as input to fused classification systems using ANFIS and HMM methods for classification of a heart murmur. The classification experiments were performed on both classifiers using the same set of features and comparison on their correct classification rate was recorded. The experimental results reveal that the selected feature set is effective to achieve the significant classification results using HMM with an accuracy of 98.7%. The computation complexity of the proposed classification system is reduced by using less number of effective features. This property of the proposed system makes it suitable to build an intelligent system that is capable of correct recognition of the heart murmurs. Data acquisition using any electronic stethoscope combined with the suggested HMM-based classification method could effectively be used as a semi-automated cognitive system to assist the cardiologists for more objective diagnosis to differentiate the normal heart sounds and the sounds with certain pathological conditions.

Although this work carefully prepared, we are still aware of its limitations and shortcomings. First of all, the research was conducted in the four classes including normal, MS, MR, and AR PCGs. It would be better if subjects suffering from mixed murmurs or other heart valve artefacts included in this work. Second, the population of the experimental group is small; only 230 subjects might not represent the majority of the population. In future, the current framework of the classification system could further be extended to include the subjects with more heart valve disorders with the addition of some new features in the current set of features.

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CONFLICT OF INTEREST

Authors declare that they have no conflict of interests.

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