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Detection and diagnosis of dilated cardiomyopathy and hypertrophic cardiomyopathy using image processing techniques

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ABSTRACT

Major heart diseases like heart muscle damage and valvular problems are diagnosed using echocardiogram. Since the echocardiogram is an image or sequence of images with less information the cardiologist spends more time to predict or to make decision. Automating the detection and diagnosis of dilated cardiomyopathy (DCM) and hypertrophic cardiomyopathy (HCM) is a key enabling technology in computer aided diagnosis systems. In this paper, a system is proposed to automatically detect and diagnose dilated cardiomyopathy (DCM) and hypertrophic cardiomyopathy (HCM). This system performs denoising, enhancement, before left ventricular segmentation is carried out in the individual frames. Using the segmented left ventricle, the LV parameters like volume and ejection fraction (EF) are calculated and also the end-diastolic LV is extracted. The PCA and DCT features are obtained from the extracted end-diastolic LV and the classifiers BPNN, SVM and combined K-NN are used to classify the normal hearts, hearts affected with DCM and hearts affected with HCM. The PCA feature with BPNN classifier gives a highest overall accuracy of 92.04% in classifying normal and abnormal hearts. Experiments over 60 echocardiogram videos expose that the proposed system can be effectively utilized to detect and diagnose DCM and HCM.

1. Introduction

The Dilated Cardiomyopathy (DCM) and Hypertrophic Cardiomyopathy (HCM) are principal types of cardiomyopathy with predominant myocardial involvement [1]. Dilated cardiomyopathy is a disease of the heart muscle, usually starting in your heart's main pumping chamber (left ventricle). The Left Ventricle pumps oxygenated blood to entire body through aorta. The amount of blood which is pumped into aorta during each cardiac cycle, referred to as Stroke Volume (SV), depends on the change produced in LV Volume. Thus the left ventricle shape plays an important role in diagnosis and therapeutic index for evaluation of cardiac diseases like cardiomyopathy. In the case of dilated cardiomyopathy the heart can't pump blood as well as a healthy heart can, since the ventricle stretches and thins (dilates), where in the case of hypertrophic cardiomyopathy the ventricular septum gets thicker. Fig. 1 shows the a) normal heart, b) Dilated Cardiomyopathy and c) Hypertrophic Cardiomyopathy. There are four types of hypertrophic cardiomyopathy namely sigmoidal, reverse curve, apical and neutral. The sigmoid type has a characteristic asymmetric basal septal myocardial hypertrophy, which results in a prominent basal septal convexity. The remainder of the septum is predominantly concave to the LV cavity. The reverse curve type is most commonly associated with genetic mutations known to cause HCM. The apical type has a characteristic apical hypertrophy. There may be an associated "apical pouch" which occurs when the very tip of the apex develops a thinned portion and may contain an apical thrombus. This finding is often associated with myocardial fibrosis and has been shown to be associated with adverse cardiovascular events. In the case of neutral type, it has a uniform or nearly uniform hypertrophy involving all myocardial walls. This type is often difficult to distinguish from hypertension-induced hypertrophy or changes related to elite athletic performance.

An echocardiogram is a type of ultrasound test that applies high-pitched sound waves that are sent by a device called a transducer. The device obtains echoes of the sound waves as they bounce off the various regions of the heart. These echoes are turned into moving pictures of the heart that can be seen on a video screen. The clinical parameters such as myocardial mass (MM), Ejection Fraction (EF) are calculated using the echocardiogram by the cardiologist to detect and diagnose heart diseases. Apical two chamber (A2C), parasternal long axis (PLAX), apical four

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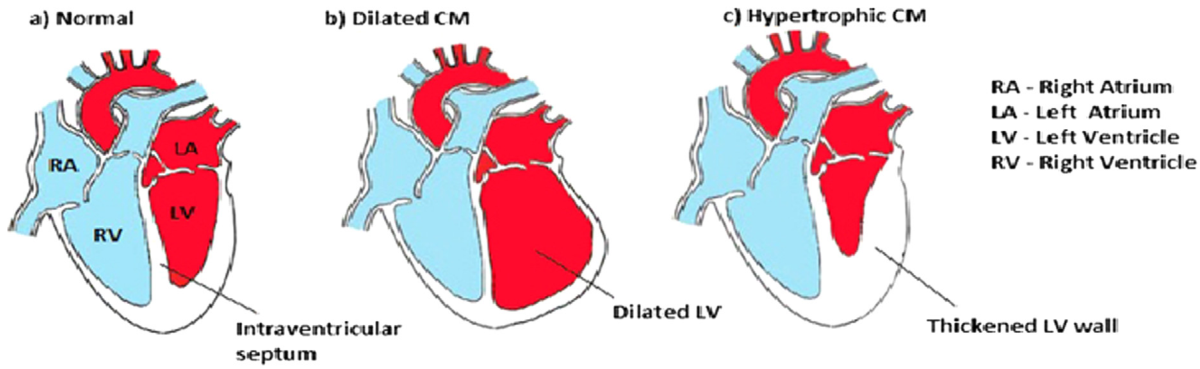

Fig. 1. Normal heart and heart affected with Dilated Cardiomyopathy.

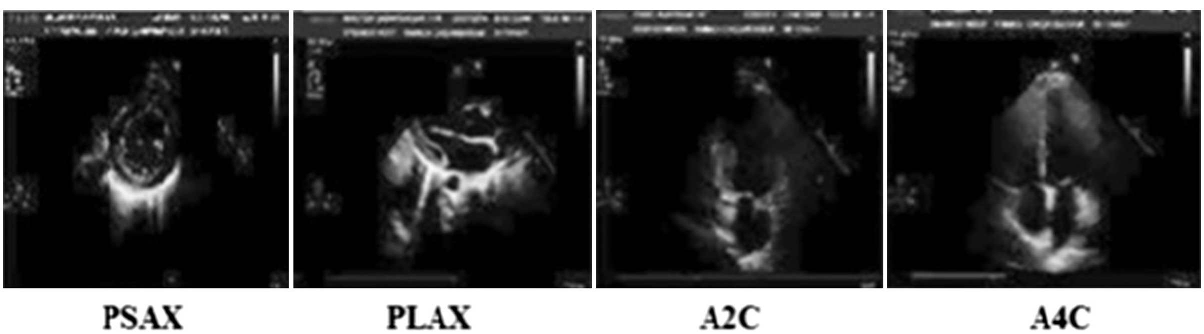

Fig. 2. Basic views in Echocardiography.

Table 1
Heart dimensions needed for this study.

	Range
LV diastolic diameter/ BSA, cm/m^2	2.2–3.1
LV diastolic volume/BSA mL/m^2	35–75
LV systolic volume/BSA mL/m^2	12–30

chamber (A4C) and parasternal short axis view (PSAX) are the four basic views in echocardiography [2] used by the cardiologist for diagnosis and are shown in Fig. 2. The measurement of LV parameters in combination with shape analysis may further provide comprehensive assessment of left ventricular performance [3]. Some heart dimensions needed for this study is illustrated in Table 1.

The paper is organized as follows: In Section 2 previous work done in this area is described, Section 3 explains the various stages involved, The experimental results are discussed in Sections 4 and 5 concludes the paper.

2. Previous work

The Echocardiogram images or image sequences often suffer with speckle noise. It degrades image contrast and block out the underlying cardiac anatomy. In order for the cardiologist to achieve correct diagnosis, the echocardiogram images have to be despeckled in [4]. Also the authors compared results of various filters in terms of mean square error, signal to noise ratio, peak signal to noise ratio, speckle index and edge preservation index. Wavelet based Thresholding for noise suppression in ultrasound videos was proposed in [5] and a PSNR value of 27 is obtained which is highest among the filters compared. Semi-automatic systems or framework to detect cardiac diseases are proposed in [8,8]. The system proposed in [7] generates first-time automatic detection of cardiovascular abnormalities using Doppler ultrasound images. The system then provides remote collaborative sharing of this information among different doctors to allow distance telediagnostics. With that system, different actors in the field of medicine (nurses, practitioners, etc.) are able to contribute to a more reliable diagnosis in the cardiovascular domain. The authors in [8] proposed a Behavior Knowledge Space fusion rule by combining neural network classifier, a Bayesian classifier, and a classifier based on hidden Markov chains. The comparative evaluation is also discussed in terms of both accuracy and required time, in which the time to correct the classifier errors by means of human intervention is also taken into account.

Automatic estimation of initial endocardial border in short axis echocardiographic sequences is based on LVCP detection and subsequent radial search with gradient magnitude and direction [9]. The authors in [10] used optical flow to estimate velocities of the left ventricular wall segments and find relation between these segments motion. Cardiac abnormality detection by automated ejection fraction calculation is proposed in our previous work [11]. Characterization of spatio-temporal motion patterns of heart regions from echocardiography sequences is used for disease discrimination in [12]. An automated system to detect and diagnose heart muscle damage from echocardiogram videos is proposed in [13], composite wall motion of left ventricle is created using short axis echo sequences and pattern recognition techniques are used to detect and diagnose the heart muscle damage. The effect of Suspension model (a two-phase model) for blood flow through catheterized curved artery with overlapping stenosis is elaborated by the authors in [14] which enables one to observe the effects of red cells concentration on flow characteristics in a catheterized artery., Graphical results are presented for the axial velocity of fluid, the wall shear stress distributions, resistance impedance and trapping.

3. Methodology

In this paper segmentation of left ventricle from parasternal short axis echocardiogram sequences is automated using which left ventricle parameters are calculated. The end-diastolic frame i.e., max? (LV) is obtained and the features of end-diastolic LV are extracted then classifiers BPNN, and SVM are used to classify the normal, DCM and HCM echocardiogram sequences. The block diagram of proposed system is shown in Fig. 3. The proposed system includes five steps namely preprocessing, segmentation, feature extraction and classification. When the echocardiogram video is given as an input to the proposed system, firstly the video is converted into frames and each frame is processed separately. Sample diastolic frames with normal and hearts affected by DCM and HCM are shown in Fig. 4.

3.1. Preprocessing

During the preprocessing step artifact present on the boundaries of the frames are removed by setting the boundary pixels to black at a width less than or equal to eighty pixels. After artifacts are removed denoising and contrast enhancement is carried out using, speckle reducing anisotropic diffusion filter (SRAD) and adaptive histogram equation respectively. After empirically analyzing numerous echocardiogram frames, the pixels on the boundaries at a width less than or equal to 80 pixels are set to black. In the next step, SRAD filter is used to remove the speckle noise present in the frame to make the segmentation process easy.

3.1.1. Statistical approach

SRAD can not only preserve edges but also enhances edges. Given an intensity $I_0(x,y)$ image inite power and no zero values over the image support ω, the output image $I(X,y;t)$ is evolved according to the following PDE:

$$\begin{cases} \frac{\partial I(x,y;t)}{\partial t} = div(c(q)\nabla I(x,y;t) \\ I(x,y;t), \left(\frac{\partial I(x,y;t)}{\partial \vec{n}}\right)|_{\partial\Omega} = 0 \end{cases} \tag{1}$$

where t represents diffusion time,$\partial\Omega$ denotes the borders of Ω, $\vec{n}$ is the outer normal to the $\partial\Omega$, and

$$c(q) = \frac{1}{1 + [q^2(x,y;t) - q_0^2 t]/[q_0^2(t)(1 + q_0^2(t))]} \tag{2}$$

where $q(x,y;t)$ instantaneous coefficient of variation determined by

$$q(x,y;t) = \sqrt{\frac{\frac{1}{2}(|\nabla I|/I)^2 - (1/4^2)(\nabla^2 I/I)^2}{[1 + (1/4)(\nabla^2 I/I)]^2}} \tag{3}$$

And $q_0(t)$ scale factor of speckle. For our images in the experiment we can define $q_0(t)$ with

$$q_0(t) \approx q_0 exp[-pt] \tag{4}$$

So the proposed iteration formula of diffusion is defined with:

$$I_{i,j}^{n+1} = I_{i,j}^n + \frac{\Delta t}{4} d_{i,j}^n \tag{5}$$

and $d_{i,j}^n$ defined with:

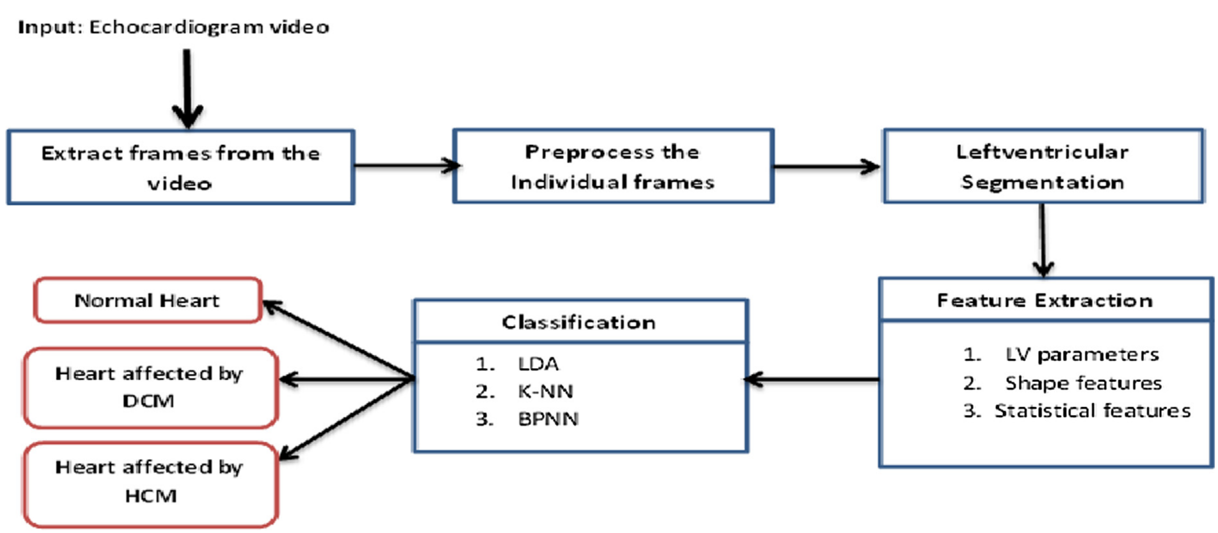

Fig. 3. Overview of the proposed system.

Fig. 4. Sample Echocardiogram frames a) Normal heart, b) Heart with DCM and c) Heart with HCM.

$$d^n_{i,j} = c^n_{i+1,j}(I^n_{i+1,j} - c^n_{i,j}) + c^n_{i,j}(I^n_{i-1,j} - c^n_{i,j}) \quad (6)$$

where ρ is a constant to slow down the decrease of q_0 while the algorithm is iterating. The sample frames after preprocessing is shown in Fig. 5.

3.2. Segmentation

Preprocessing of frames is followed by segmentation of left ventricle. Fig. 6 shows the steps in segmenting the region of interest (left ventricle).

FCM clustering [20] is used to partition N objects into C classes. In our method, N is equal to the number of pixels in the image i.e. $N = X \times Y$ and C = 3 for 3-class FCM clustering. The FCM algorithm uses iterative optimization of an objective function based on a weighted similarity measure between the pixels in the image and each of the C-cluster centers. After performing FCM clustering, finally each pixel is assigned to the cluster for which its membership value is maximum. Based on the intensity distribution obtained using histogram of the image, the threshold value is calculated by taking the mean of maximum of cluster 1 and minimum of cluster 2 or maximum of cluster 2 and minimum of cluster 3. This method of threshold selection takes into account the intensity distribution in the image. This choice helps in obtaining optimum threshold values for different images obtained under different conditions. The result of FCM thresholding is shown in Fig. 7. To obtain the cardiac cavity (left ventricle), the connected components in the resultant image is labeled using the connected component labeling (CCL). The central connected component that corresponds to the LV is extracted and area of LV is calculated for each individual frame. The LV having the maximum area ie., the diastolic LV is alone is derived and super imposed with the preprocessed frame before feature extraction is carried out. The extracted diastolic normal, dilated and hypertrophic left ventricles are shown in Fig. 8.

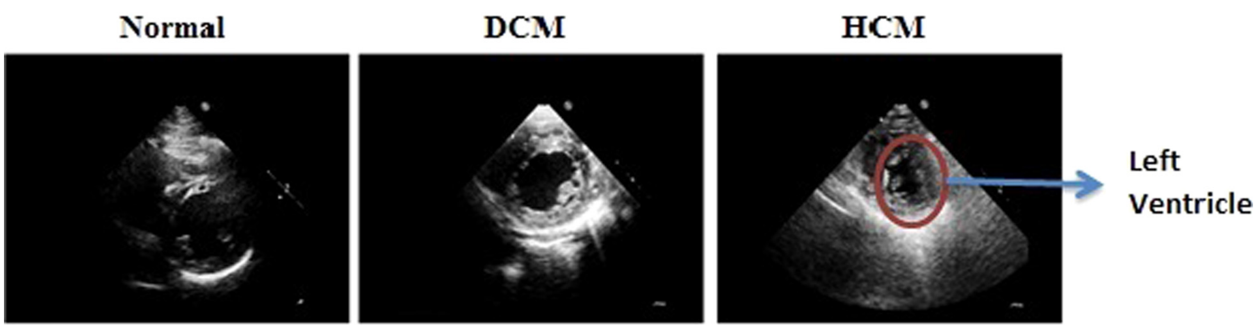

Fig. 5. Sample preprocessed frames.

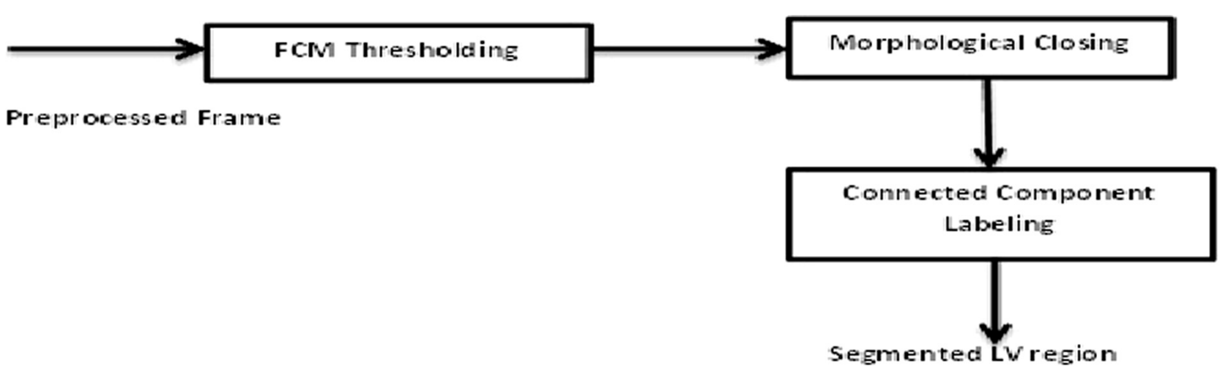

Fig. 6. Steps in segmentation process.

Fig. 7. Result of FCM thresholding.

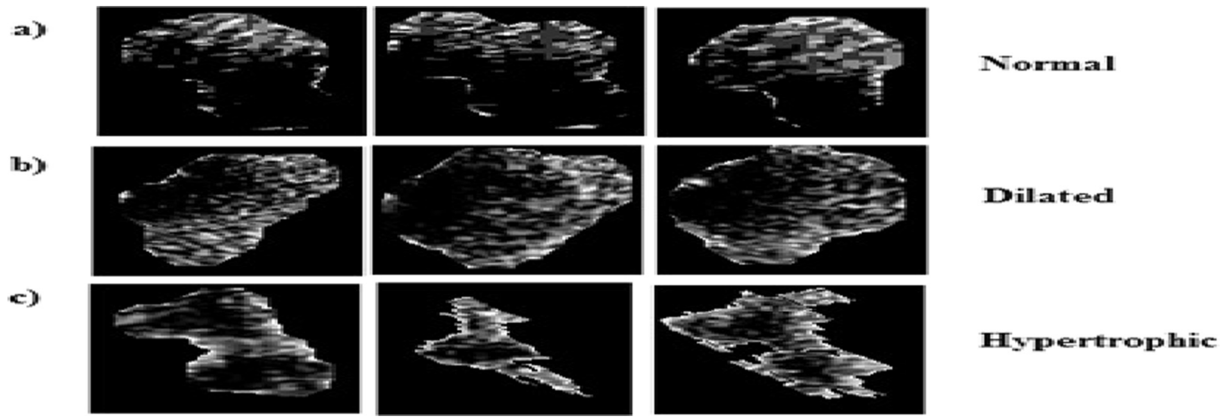

Fig. 8. Sample normal, dilated and hypertrophic left ventricles extracted.

3.3. Feature extraction

The extracted LV region alone is cropped and resized to 150×150 in order to make the feature extraction and classification easier. The parameters like left ventricular volume and ejection fraction are extracted from the segmented LV. Also two significant features viz, principal component analysis and discrete cosine transform are extracted and used.

The Volume of the LV can be calculated as follows

$$Volume = 7.0/(2.4 + D)D^3 \tag{7}$$

where '*D*' is the equivalent diameter,

The end diastolic volume (EDV) is the largest LV volume of the cardiac cycle. The end systolic volume (ESV) is the smallest LV volume of the cardiac cycle, the difference between them gives the stroke volume (SV) ie. (EDV-ESV), and the ratio of stroke volume to the end diastolic volume gives the ejection fraction and is given by

$$LVEF = (EDV - ESV)/EDV \tag{8}$$

$$LVEF = SV/EDV \tag{9}$$

where, SV = EDV-ESVred LVEF is commonly used by cardiologist to classify normal and abnormal hearts [23,22]. The cut-off values of various LV parameters are illustrated in the following Table 2.

PCA is a popular technique for multivariate statistical analysis and finds application in many scientific fields. The main goal of PCA is to reduce the dimensionality of the data from N dimensions to M. This is obtained by transforming the interrelated variables of the data set to uncorrelated variables, the principal components, in a way that as much of the variation of the data set is retained. The principal components are ordered in a way that the variation explained by each of them is in descending order [15]. This means that the first principal components explain most of the variation in the data and by using those we can project the data in lower dimensions. It has been shown that the principal components can be computed by finding the eigenvalues-eigenvectors of the covariance matrix of the data. Once the eigenvalues-eigenvectors are calculated, the eigenvectors are sorted in descending order based on their eigenvalues and then the first M eigenvectors can be used to project the data in lower dimensions.

Table 2
Cuttoff values of various LV parameters.

LV parameter	Cutoff value
LV ejection fraction (%)	40
LV mass (g/m^2)	90
LV diastolic volume (mL)	76
LV systolic volume (mL)	31
Septal Thickness (cm)	1

3.3.1. Discrete cosine transform (DCT)

The discrete cosine transform (DCT) [16] also attempts to decorrelate the image data as other transforms. After decorrelation each transform coefficient can be encoded independently without losing compression efficiency. It expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. The DCT coefficients reflect different frequency component that are present in it. The first coefficient refers to the signal's lowest frequency (DC component) and usually carries the majority of the relevant information from the original signal. The coefficients present at the end refer to the signal's higher frequencies and these generally represent the finer details. The rest of the coefficients carry different information levels of the original signal. The DCT of the image is as the same size as that of the original image. The DCT of the image is converted into a one dimensional vector by zigzag scanning, so that the components are arranged according to increasing value of frequency.

3.4. Classification

The extracted features are fed to the support vector machine, back propagation neural network and combined K- nearest neighbor classifiers to classify the normal heart and heart affected by DCM or HCM. The BPNN, combined K-NN and SVM classifiers are chosen since they give promising outcomes in medical image analysis. Further these classifiers are utilized in this study to see how the extracted features are helpful in accurate classification of normal and abnormal hearts using both supervised and unsupervised pattern classification methods.

3.4.1. Back propagation neural network (BPNN)

The back propagation networks are typically multi-layer artificial neural network, usually with an input layer, one or more hidden layers and an output layer. For the hidden layer neurons, to serve any useful purpose, they must have non-linear activation (or transfer) function. The most common non-linear activation functions include the: log-sigmoid, tan-sigmoid, Gaussian and softmax transfer functions. In a back propagation neural network (BPNN), learning is formulated as follows. Firstly, a training pattern is presented to the input layer of the BPNN. The network propagates the input pattern from layer to layer until the output pattern is generated by the neurons in the output layer. If the output pattern is different from the desired output, an error is calculated. This

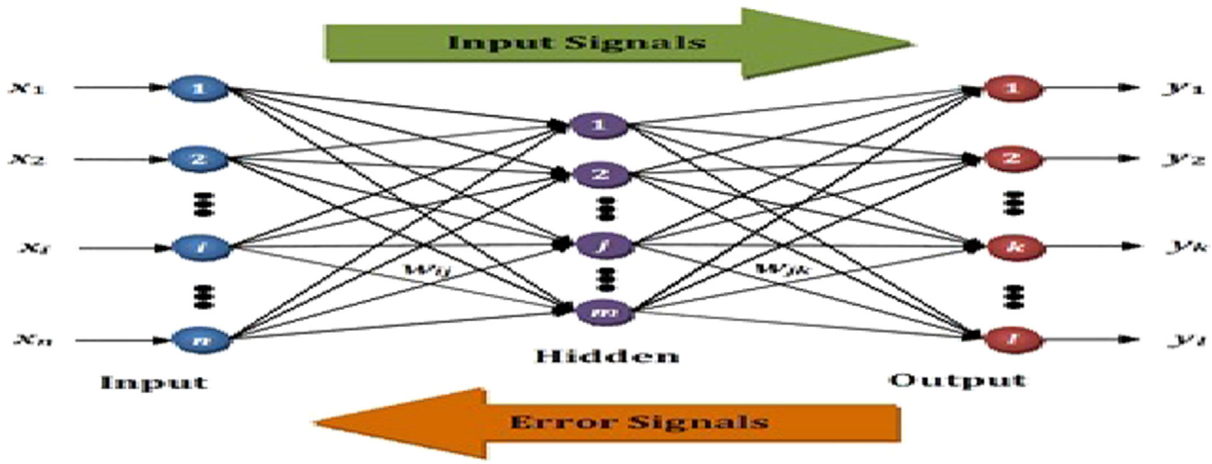

Fig. 9. A typical architecture of a BPNN.

error is then propagated backwards through the network to the input layer. As the error is propagated backwards, the weights connecting the neurons are adjusted by the back propagation algorithm. Fig. 9 shows a typical architecture of a BPNN [17].

3.4.2. K-nearest neighbour

The K-NN classifier [18], is one of the oldest and simplest supervised learning which uses distance between objects for classification, though simple, it frequently gives competitive outcomes. The K-NN classifier separates unlabeled pattern by the majority label between its K-nearest neighbors. In this study the distance between two objects is calculated using Euclidean distance, Mahalanobis distance and city block distance, then the results are combined to form a decision. The combined K-NN classifier is shown in Fig. 10.

3.4.3. Support vector machine (SVM)

Support vector machine is a supervised learning algorithm. From the training samples SVM tries to models two different classes. The principle of SVM is to find the hyperplane which maximizes the distance between the two classes. The hyperplane generated depends on the samples which are a subset of the two classes. The samples which lie near the hyperplane are called support vectors. Support vectors are the training samples that determine the optimum separating hyperplane and are hard patterns to classify. When the training samples are linearly separable it is easy to classify them, however when the samples are linearly inseparable then the kernel function is used to separate the two classes. Some common kernels are Gaussian radial basis function, polynomial (inhomogeneous), polynomial (homogeneous) and sigmoid kernel. In this work polynomial and radial basis function kernel of SVM is used. The outcomes of the classifiers are discussed in the following Section.

4. Results and discussions

This study includes 20 normal, 30 DCM, and 10 HCM echocardiogram videos taken by using Philips iE33 xMATRIX echo system from the Department of Cardiology, Raja Muthaiah Medical College Hospital, Annamalai University. The videos are up to 4–6 s having around 46 fps. The resolution of the frame is 1024×768 pixels. SRAD filter employed in this work in the preprocessing step removes speckle noise better when compared to other filters which could be seen in terms of PSNR value shown in Table 3.

The segmentation performance is evaluated based on four qualitative metrics namely rand index (RI), variation of index (VOI), boundary displacement error (BDE) and global consistency error (GCE). Rand index tallies the portion of set of pixels whose labeling are reliable between the ground truth and the computed segmen-

Table 3
Comparison of PSNR values.

Denoising filter	PSNR value	Reference
Wavelet	29.14	[18]
Wiener	32.14	[19]
High boost filter	33.16	[13]
SRAD filter	**44.21**	**Proposed method**

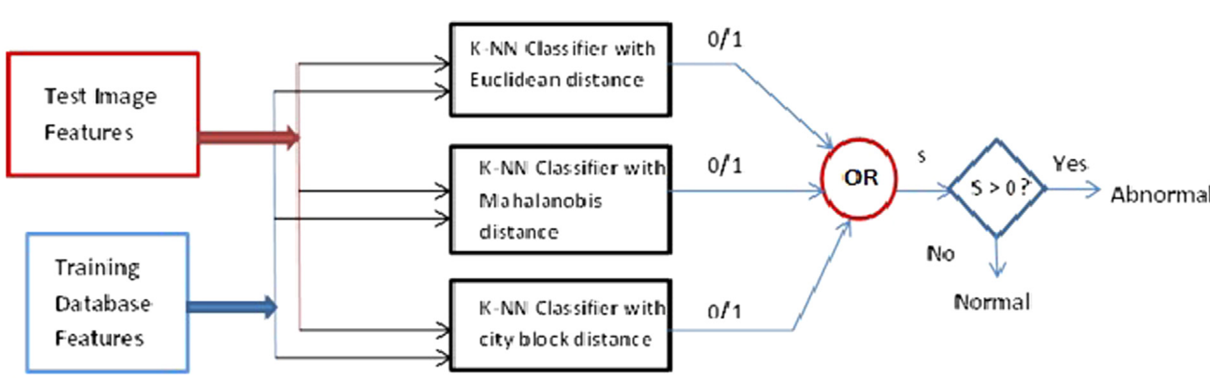

Fig. 10. Combined K-NN classifier.

tation averaging over various ground truth segmentation. The global consistency error (GCE) evaluates the level to which one segmentation can be seen as a finesse of the other. The boundary displacement error (BDE) measures the average displacement error of one boundary pixels and the closest boundary pixels in the other segmentation. The variation of information (VOI) characterizes the separation between two segmentations as average conditional entropy of one segmentation given by the other, and hence evaluates the quality of entropy in one segmentation which cannot be described by the other. In general the high value of RI and lower value of BDE, GCE and VOI indicates that the segmentation is better (Fig. 11).

Table 4 gives the comparison of various segmentation performance metrics of the proposed method with that of existing methods. It can be seen that the RI value is higher and GCE, BDE and VOI values are lower for the proposed method. Also the automatically detected LV boundaries coincide with manually drawn boundaries by cardiologist, which assures the accuracy of the segmentation. Fig. 10 shows the automatically and manually drawn boundaries of all the three cases, normal, DCM and HCM.

From the segmented the LV parameters such as volume, ejection fraction are calculated. It can be observed that the change in volume of LV of heart affected by DCM during a cardiac cycle is less than the normal heart and heart affected with HCM and this shows the changes induced by dilated cardiomyopathy in the functioning of heart. The left ventricular volume of a sample normal heart, DCM heart and HCM heart is compared in Fig. 12 and their corresponding ejection fraction are 66% for normal heart, 15.2% for heart affected with DCM and 66% for heart affected with HCM. The LVEF alone cannot be used for classification since most of the mild cases

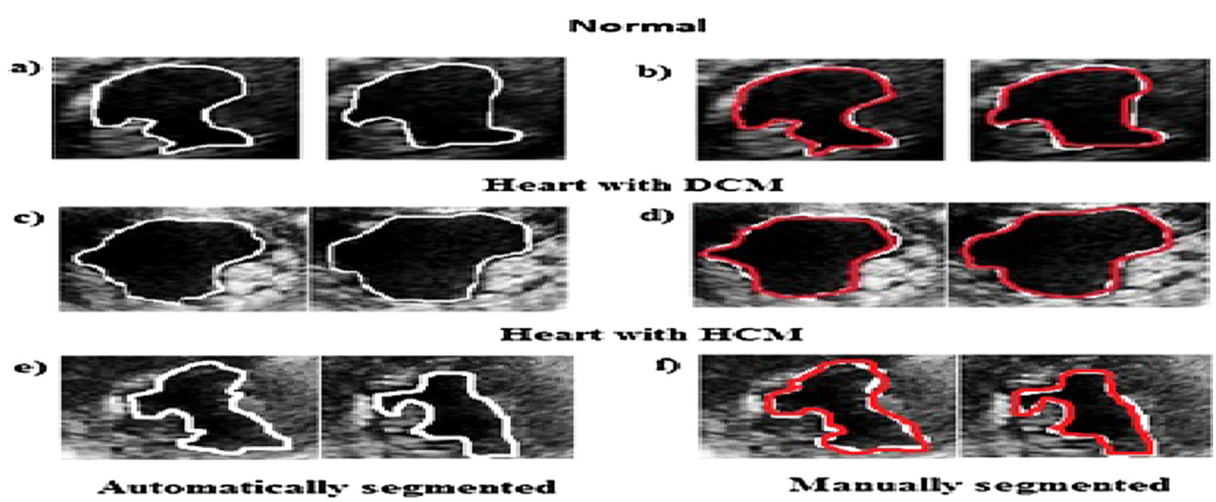

Fig. 11. a) and b) LV boundaries automatically and manually segmented normal heart, c) and d) LV boundaries automatically and manually segmented heart with DCM, e) and f) LV boundaries automatically and manually segmented heart with HCM.

Table 4
Segmentation performance metrics.

Methods	Reference	RI	GCE	BDE	VOI
Morphological operations + Connected component labeling	[13]	0.9289	0.048	0.4801	0.4437
K-means clustering + active contour	[18]	0.9308	0.0401	0.4356	0.4348
FCM + Morphological operations	**Proposed method**	**0.9545**	**0.031**	**0.3214**	**0.4008**

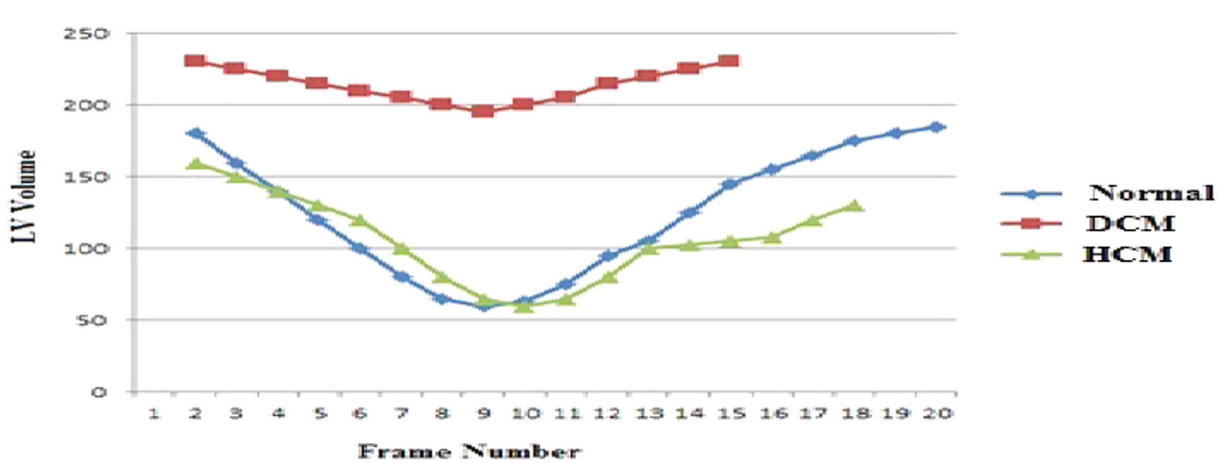

Fig. 12. LV volumes of normal, hearts with DCM and HCM.

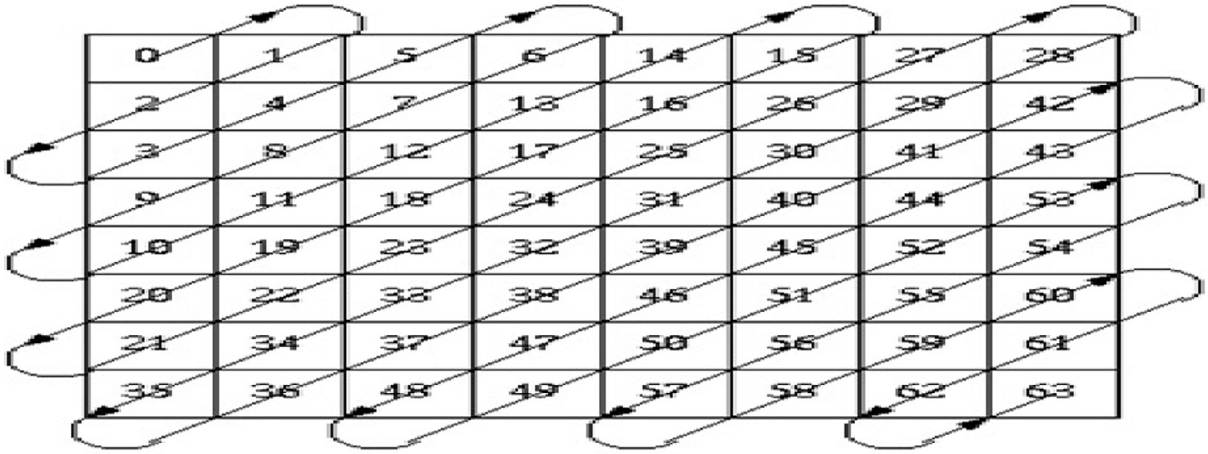

Fig. 13. Zigzag algorithm.

and some of the moderate cases have normal ejection fraction values i.e., EF$\geqslant$ 40%.

The segmented LV region of diastolic frame alone is used for feature extraction as it contains useful information compared to other frames. The region of LV alone is cropped and resized to 100×100 in order to make the feature extraction easier. While extracting the DCT features zigzag algorithm is used to create a feature vector with increasing frequency values. The concept of zigzag algorithm is illustrated in the Fig. 13. The extracted features are fed to the classifiers BPNN, SVM and combined K-NN to classify the normal heart and heart affected by DCM or HCM.

The performance measures sensitivity, specificity, negative predictive value, positive predictive value, Mathews cross correlation and accuracy, are computed using the equations and the confusion matrix shown in Table 5 is used to calculate these measures.

$$Sensitivity = tp/(tp + fn) \tag{10}$$

$$specificity = tn/(fp + tn) \tag{11}$$

$$Accuracy = (tp + tn)/(tp + fp + tn + fn) \tag{12}$$

$$MCC = \frac{(tp * tn) - (fp * fn)}{\sqrt{(tp + fp) * (tp + fn) * (tn + fp) * (tn + fn)}} \tag{13}$$

$$Negative\ Predictive\ Value = tn/(tn + fn) \tag{14}$$

$$Positive\ Predictive\ Value = tp/(tp + fp) \tag{15}$$

Table 5
Confusion matrix.

Actual	Predicted Positive	Negative
Positive	True Positive (tp)	False Positive (fp)
Negative	False Negative (fn)	True Negative (tn)

where, fp, fn, tp and tn predicted values with respect to actual values.

The sensitivity and specificity are the two significant metrics employed in medical image analysis. Sensitivity measures the fraction of the normal hearts (actual positives) which are correctly predicted. Specificity denotes the fraction of the abnormal hearts (actual negatives) which are correctly prognosticated. The positive predictive value (PPV) is the fraction of the predicted normal hearts (positive) which are correct. The negative predictive value (NPV) stands for the fraction of the abnormal hearts (negative) predictions which are right. Accuracy is generally considered as a balanced metric whereas specificity handles only negative cases and sensitivity handles only positive cases. The Mathews Correlation Coefficient (MCC) is calculated to get a better picture of the performance of the classifier, since the number of samples in the two classes is unbalanced. When compared to accuracy, MCC is used in cases where the number of samples in each of the classes differs considerably.

The back propagation neural network gave a higher accuracy when the PCA feature is passed as an input to the classifiers. When DCT is passed as an input to the classifiers the combined K-NN classifier performs better than SVM and BPNN classifiers. The performance of the three classifiers with PCA and DCT are tabulated in Table 6. The overall performance is higher for BPNN classifier with PCA features at an accuracy of 90.2%. The combined K-NN classifier with DCT feature gave the second highest performance with an accuracy of 88.94%. Higher values of NPV and sensitivity of BPNN with PCA, indicates that it is quite successful in classifying the normal hearts, the hearts affected by DCM and hearts affected with HCM as could be seen in the graph shown in Fig. 14. The proposed system performs well in classifying the hearts affected by DCM than the hearts affected by HCM, this may be due to the variation of shape i.e., the shape of normal LV and DCM affected heart's LV are discriminant.

Table 6
Performance of BPNN, SVM and comb. K-NN classifiers.

Feature	Classifier	Accuracy	Sensitivity	Specificity	PPV	NPV	MCC
PCA	BPNN	**90.20**	**85.71**	**92.54**	**85.71**	**92.54**	**78.25**
	SVM	88.50	84.29	90.77	83.10	91.47	74.81
	Comb. K-NN	87.88	82.86	90.63	82.86	90.63	73.48
DCT	BPNN	86.80	81.43	89.76	81.43	89.76	71.90
	SVM	78.95	66.67	84.62	66.67	84.62	51.28
	Comb. K-NN	88.94	84.29	91.47	84.29	91.47	75.76

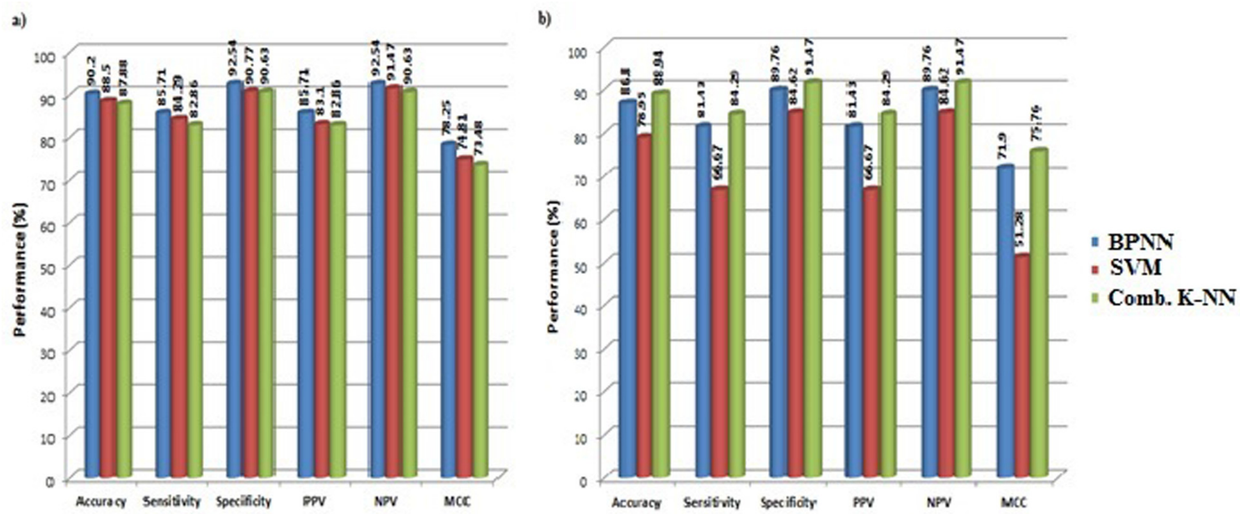

Fig. 14. Performance of BPNN, SVM and comb. K-NN classifiers in classifying normal and abnormal hearts.

5. Conclusion

In this paper a system is proposed to automatically detect and diagnose hearts with dilated cardiomyopathy and hypertrophic cardiomyopathy. The segmentation of left ventricle in echocardiogram sequences is automated from which LV parameters, DCT and PCA reduced features are extracted. The classification is done using back propagation neural network, support vector machine and combined K-NN classifiers. The BPNN classifier with PCA feature gave the better performance in classifying the normal, hearts affected by DCM and hearts affected by HCM. Hence the proposed system can be used as an effective tool for detecting and diagnosing hearts affected with dilated cardiomyopathy and hypertrophic cardiomyopathy. In future, content based video retrieval systems can be added to the system and larger dataset can be used to improve the efficiency of the system.

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