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Deep learning-based system to predict cardiac arrhythmia using hybrid features of transform techniques

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ABSTRACT

An early and accurate detection of arrhythmias is essential reduce the mortality rate due to cardiac diseases. Manual screening of the electrocardiogram (ECG) signals are time consuming, strenuous, and liable to human errors. This article proposes a deep learning approach for automated detection of cardiac arrhythmia using RCG signals fro MIT-BIH database. Various decomposition techniques namely: discrete wavelet transform (DWT), empirical mode decomposition (EMD) and variational mode decomposition (VMD) are used to de-noise the ECG signal. The time-frequency based multi-domain features are extracted from the various coefficients of the sub-bands from de-noised signals. These obtained features are ranked based on Chi-squared test and particle swarm optimization (PSO) based methods to select the best informative features for better classification accuracy. The hybrid features was classified with deep neural network (DNN) with ten-fold cross validation strategy in classifying five types of ECG beats. The best results was obtained with an accuracy of 99.75% with less computational complexity of 0.14 s using Chi squared selection approach. Thus the proposed model can be used in the hospitals set-up to automatically screen the abnormal ECG beats.

1. Introduction

Globally, the average death rate due to cardiovascular disease (CVDs) is about 235 per 100,000 population, but in India this rate is slightly higher which is about 272 per 100,000 (Prabhakaran et al., 2016). Early detection using automated analysis of electrocardiogram (ECG) signals can save life and help to provide timely treatment for the cardiac disease patients (Sameni et al., 2007). Movement of electrodes, and muscle tremors causes noise and artifacts in the ECG signals. Various filters need to be used to pre-process these ECG signals and then related features can be extracted from them (Ebrahimzadeh et al., 2015; Zhang et al., 2019). Nowadays, different hybrid feature approach based on time-frequency methods have been used for arrhythmia detection (Adnane & Belouchrani, 2017; Qurraie & Afkhami, 2017). Decomposition of ECG can be done by using discrete wavelet transform (DWT), which provides adequate information of the original signal in both time-frequency domain (Addison, 2005; Sahoo et al., 2017; Singh & Tiwari 2006). A wavelet transforms detection system used for detect QRS complexes, a complex onset and end points in a single-lead ECG signal (Martinez et al., 2005). Different systems based on multi-resolution WT transform, dominant rescaled wavelet coefficients (DRWC), and discrete wavelet are used effectively for detecting R-peaks and QRS complexes (Ghaffari et al., 2008; Pal & Mitra, 2010; Tantawi & Revett, 2015).

The Hilbert-Huang transform (HHT) combine with wavelet transform produces better detection results in finding the QRS complex in ECG signal (Übeyli, 2008; Yan & Lu, 2014). A review article highlighted the importance of empirical mode decomposition (EMD) and ensemble-EMD (EEMD) technique in denoising the ECG signal which removed the noise, powerline interference and baseline wander from the ECG signal (Han et al., 2017). The methods that combine the DWT and EMD approach is an effective time resolution analysis and provides better results in detecting the QRS complex and other waves of the ECG signal (Kabir & Shahnaz, 2012; Nimunkar &, Tompkins, 2007; Rabbani et al., 2011). Slimane et al. (2010) reported better accuracy rate in detecting the QRS complex using EMD on ECG taken from MIT–BIH database. In a recent article, better detection accuracy of 95.22% is achieved in detecting myocardial infarction (MI) based on convolutional

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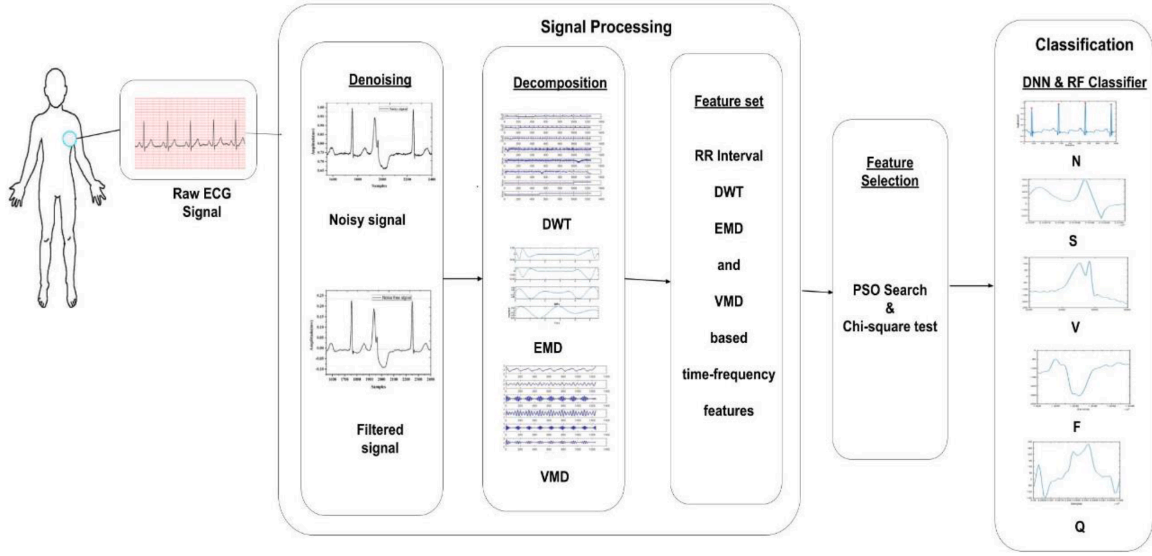

Fig. 1. Block diagram of the proposed methodology.

neural network (CNN) algorithm (Acharya et al., 2017). In a combined approach that includes EMD and EEMD for feature extraction that produced an accuracy of 99.20% and sensitivity of 98.01% in classifying five types of ECG beats using sequential minimal optimization-support vector machine (SMO-SVM) classifier (Kandala & Dhuli, 2017). Suchetha et al. (2017) introduced a better approach based on EMD for effective analysis of non-stationary signals like ECG signal but it produced high computational time. Dragomiretskiy and Zosso (2014) proposed the variational mode decomposition (VMD) model to overcome the limitations of EMD process to decompose the ECG signals. Maji et al. (2015) used VMD technique for decomposition of ECG signal which produced good results in detecting ventricular QRS complex. Recently, it is shown that combination of EMD and VMD techniques are effective in de-noising and detecting the arrhythmia beats in ECG signals (Acharya et al., 2017; Chang, 2010; Jovic & Bogunovic, 2012; Mert, 2016). Also, it is shown that the hybrid feature set improves the accuracy of cardiac arrhythmia detection (Anwar et al., 2018).

In recent works, deep learning methods are found to be more effective in classifying arrhythmia beats than the traditional machine learning approaches (Kim et al., 2020). Sannino and Pietro (2018) proposed a deep learning method to classify the ECG beats and achieved an accuracy of 99.09%. Yıldırım et al. (2018) used 1D-CNN model to classify 17 arrhythmia classes and reported an accuracy of 91.33%. Shi et al. (2020) presented a combination of CNN and long short-term memory (LSTM) network for arrhythmia classification. They extracted heartbeat and RR interval features for the classification and reported an accuracy of 99.26% under class-oriented scheme. Hannun et al. (2019) developed a deep neural network (DNN) using 91,232 single-lead ECGs where they achieved an area under the receiver operating characteristics curve (ROC) of 0.97. Isin and Ozdalili (2017) developed a deep learning model to classify the ECG betas and reported an accuracy of 92%. Wu et al. (2021) proposed an efficient 12-layer deep I-D CNN for classifying the five micro-classes of heartbeat types by using the MIT- BIH Arrhythmia database. The signals are de-noised with wavelet self-adaptive threshold method and then classified. The results are compared with neural network, random forest, and other CNN networks. It is found that the proposed method resulted better performance in terms of accuracy of 97.41 with anti-noise capability. Li et al. (2022) developed a deep learning model to classify ECG signal using hybrid features set consisting Q, R, and S complex features for arrhythmia detection. They classified the hybrid set with a 1-D convolutional neural network (CNN) and achieved an accuracy of 98.98%.

In this work we have proposed an automated ECG classification system for arrhythmia detection using hybrid feature set. Initially the ECG signal is decomposed by various transformed methods like DWT, EMD and VMD and then the time-frequency domain features were extracted from the decomposed signal and combined the individual features to make a hybrid feature set having large data size. The extracted informative features from various coefficients of the sub-bands are ranked by Chi-square test and PSO search methods to select the best informative feature that will improve the classification accuracy. The ranked features are then classified with random forest and deep neural network classifiers to classify the arrhythmia beats and compared the results with few published articles.

2. Material and methods

2.1. ECG database

In this study, we have used the ECG records of both normal and life-threatening arrhythmias taken from MIT-BIH arrhythmia database. The source file of the database was obtained from Beth Isreal Hospital Arrhythmia Labortory (Moody & Mark, 2001). It consists 48 thirty-minute ECG signals of two-channel ambulatory recordings, where each signal is bandpass filtered at 0.1–100 Hz and sampled at 360 Hz. The database was separated into two groups where one group contains record numbered from 100 to 124 (23 recordings with some number missing) randomly selected from a mixed population and remaining signals from 200 to 234 (25 recordings with some number missing) belongs to other group. There are 116,137 QRS complexes in the database. Each record in the database has two leads where 45 files have modified lead II, 40 files have V1, and II, V2, V4 and V5 is distributed over 11 recordings. According to Association for the Advancement of Medical Instrumentation (AAMI) recommendation the MIT-BIH arrhythmia database are combined to have five classes. The AAMI recommended classes are N (normal and bundle branch block beat types), S (supraventricular ectopic beats), V (ventricular ectopic beats), F (fusion of normal and VEBs), and Q (unknown beats including paced beats).

2.2. ECG signal analysis

In any ECG automated process, data analysis consists of de-nosing, detection of peaks, feature extraction and classifications of cardiac arrhythmias. Initially, ECG signals are de-noised with wavelet transform and R-peaks and QRS complexes are detected from each heart beat (Kabir & Shahnaz, 2012). Fig. 1 represents the block diagram of detailed proposed ECG beat classification scheme. After detection of QRS complex a window of 260 samples (130 samples before and after of R_{loc}) is selected to get a cardiac cycle.

2.3. Hybrid features

Extracting and selecting the appropriate time-frequency domain feature improves the performance of the classifier. Direct and transformation methods are used to transform the features. The direct features extraction method consists of features namely on/off peaks, width and height of QRS complex and heartbeat intervals, whereas time-frequency features are derived from the transformation methods. The feature set consists of two heartbeat interval features, four temporal, twenty wavelet transforms, six EMD and twelve VMD features, were used for classification.

2.3.1. Discrete wavelet transforms (DWT)

The time-frequency localization of DWT makes it suitable for non-stationary signals like ECG (Kirst et al., 2011). After segmentation of ECG signal, DWT is applied with a selected window to obtain the discriminating morphological features. In DWT, the signal is decomposed based on scaling and shifting functions using the mother wavelet and expressed as

$$\psi_{p,q}(t) = \frac{1}{\sqrt{p}}\psi\left(\frac{t-q}{p}\right) \tag{1}$$

where p, q ε R, $p > 0$, and R is the wavelet space.

The wavelet transform of a signal $\mathrm{y(n)}$ is expressed as

$$y(\mathrm{m,n}) = \sum_{t=-\infty}^{\infty} \mathrm{y(n)} \times \psi_{\mathrm{m,n}}(\mathrm{n}) \tag{2}$$

The DWT of a signal x is calculated convoluting it with a low pass filter having impulse response m resulting:

$$y[n] = (x * m)[n] = \sum_{k=-\infty}^{\infty} x[k]m[n-k] \tag{3}$$

$$y_{low}[n] = \sum_{k=-\infty}^{\infty} x[k]m[2n-k] \tag{4}$$

$$y_{high}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n-k] \tag{5}$$

Daubechies 6 (db6) based wavelet function was used to decompose the ECG signals up to nine levels with detail coefficients (D1-D9) and approximation coefficient (A9). We have considered the first five level decomposed signals as it contains maximum clinical information of the ECG signal. We have extracted statistical features such as maximum, minimum, mean and standard deviation of each sub bands. A total of twenty features were extracted from each wavelet coefficients.

$$\begin{aligned} \mathit{DWT\ features} : \{ & \wedge \mathrm{D1}, \vee \mathrm{D1}, \mu\mathrm{D1}, \sigma\mathrm{D1}, \wedge\mathrm{D2}, \vee\mathrm{D2}, \mu\mathrm{D2}, \sigma\mathrm{D2}, \wedge\mathrm{D3}, \vee\mathrm{D3}, \\ & \mu\mathrm{D3}, \sigma\mathrm{D3}, \wedge\mathrm{D4}, \vee\mathrm{D4}, \mu\mathrm{D4}, \sigma\mathrm{D4}, \wedge\mathrm{A4}, \vee\mathrm{A4}, \mu\mathrm{A4}, \sigma\mathrm{A4}\} \end{aligned}$$

where $\wedge$ is minimum, $\vee$ is maximum, μ is the mean and σ is the standard deviation.

2.3.2. Empirical mode decomposition (EMD) features

It is suitable for the analysis of non-stationary and non-linear signals. It decomposes the signal into a finite number of intrinsic mode functions (IMFs) which contains oscillation information of the signal (Huang et al., 1998; Kaergaard et al., 2016). Each IMFs are symmetric with respect to its local mean and also having same number of zero crossings and extrema. By the iterative process, the IMFs are found at each scale going from fine to coarse. Finally, the signal $s(t)$ is expressed as

$$s(t) = \sum_{i=1}^{N} IMF_i\ (t) + rN(t) \tag{6}$$

where the N is the number IMFs with zero means; $rN(t)$ is the final residue with low frequency levels. Two consecutive sifting results used for calculating the standard deviation (SD) and also used to stop the sifting process. It is given by the equation

$$SD = \sum_{t=0}^{N} \frac{|L_{i-1}(t) - L_i(t)|^2}{L^2{}_{i-1}(t)} < \varepsilon \tag{7}$$

where i is the index of the ith difference between the signal s (t) and the envelope mean e (t). The term ε is a pre-determined value for stopping the process.

In this work, the processed ECG signal is decomposed up to 4th level with equal data length of IMF1, IMF2 IMF3, and IMF4. The 2nd and 3rd IMFs are considered for selecting feature vector as it contains maximum information of the signal. The following statistical features are extracted from the decomposed signals:

$$\mathrm{Mean}(\mu) = \frac{1}{1}\sum_{j=1}^{1} \mathrm{y(j)} \tag{8}$$

$$\mathrm{Variance}(\sigma) = \sqrt{\frac{1}{1}\sum_{j=1}^{1} (\mathrm{y(j)} - \mu)^2} \tag{9}$$

$$\mathrm{Skewness}(\beta) = -\frac{1}{1}\sum_{j=1}^{1}\left(\frac{\mathrm{y(j)} - \mu}{\sigma(1)}\right)^3 \tag{10}$$

where l is the length of IMF. A total of six feature vector can be extracted from IMF_2 and IMF_3.

$$\text{EMD features} = \{\mu_{12}, \sigma_{12}, \beta_{12,}\ \mu_{13}, \sigma_{13}, \beta_{13}\}$$

2.3.3. Variational mode decomposition (VMD)

Sensitivity to noise and sampling are the main limitations of EMD process. In EMD, ECG signals are decomposing recursively from high to low frequency with different IMFs, however VMD decomposes the signals into different modes non-recursively with reverse frequency order with EMD. In VMD, the signals are decomposes into different modes from low to high around their center frequency and the original signal is reconstructed collectively (Dragomiretskiy & Zosso, 2014). A detail mathematical description of VMD method is given as:

$$\min\left\{\sum_l \left\| \partial_t\left[\left(\sigma(t) + \frac{j}{\pi t}\right) * u_l(t)\right] e^{-jw_l t} \right\|_2^2\right\} \tag{11}$$

Subject to

$$\sum_l u_l(t) = p(t)$$

where the input signal is $p(t)$, $w_l(t)$ is the center frequency. $\{u_l\} = \{u_1, u_2, \ldots\ldots.. u_l\}$ is the decomposed mode and $\sigma(t)$ *is* the dirac distribution. Langragian multipliers and quadratic penalty are introduced for reconstructing the signal. The low-frequency components is represented for higher order component of u. The signal is decomposed into four different modes (mode 1 to mode 4) w.r.t center frequency. The higher tuning parameter of WT is overcome by VMD, as fewer tuning parameters are considered for decomposition. At higher mode, it separates high frequency components hence the signal is not affected by noise. Any changes at the start and end points of the signal is accurately detected. Due to these advantages, VMD method is a suitable option to eliminate noise and extracting informative features. The following statistical features (mean, variance and skewness) are extracted from

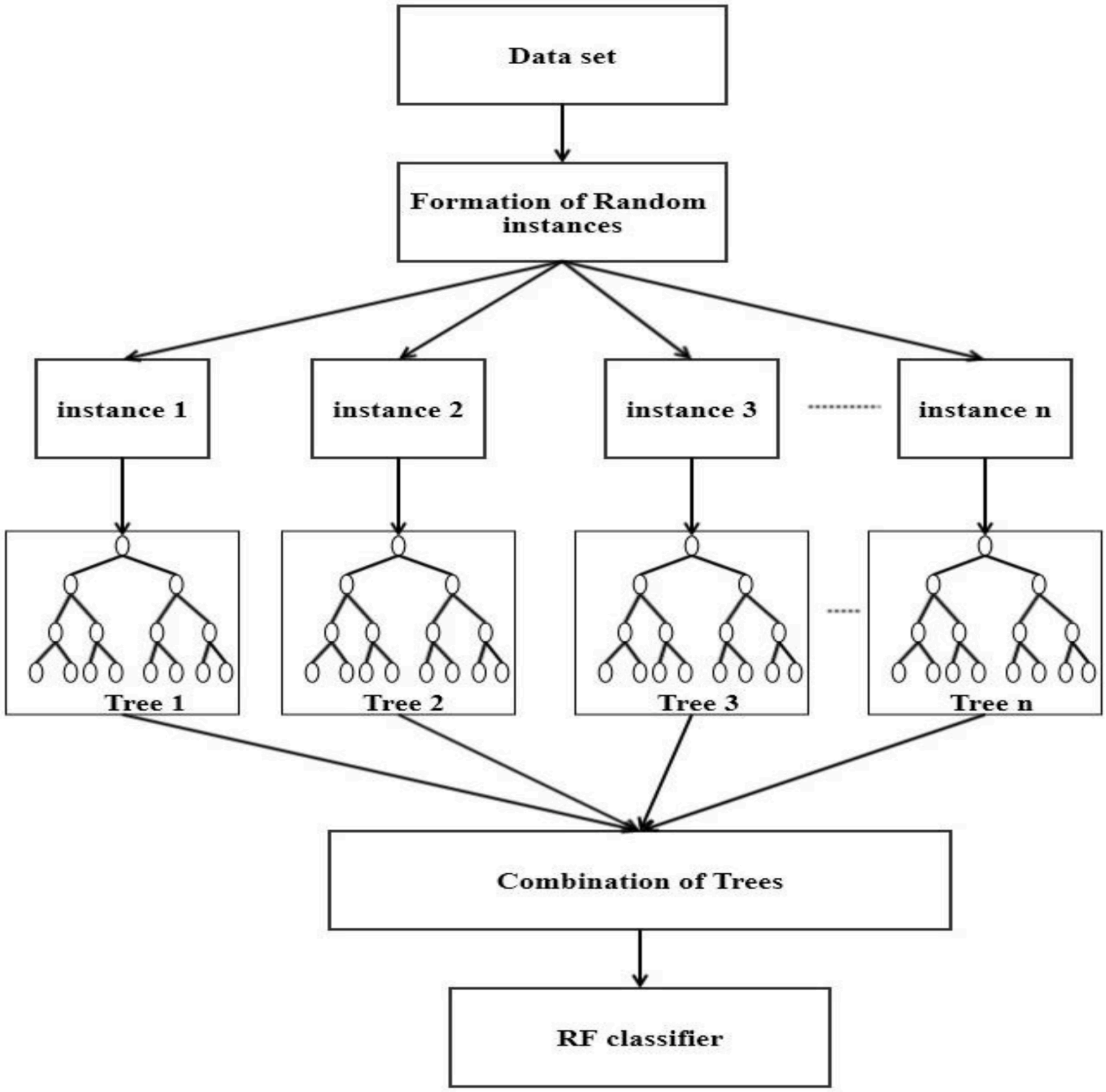

Fig. 2. Structure of the proposed RF classifier.

mode-1 to mode-4 from decomposed signal.

$$\textit{Extracted VMD features} = \{\mu \text{m1}, \text{sm1}, \beta \text{m1}, \mu \text{m2}, \text{sm2}, \beta \text{m2}, \mu \text{m3}, \text{sm3}, \beta \text{m3}, \mu \text{m4}, \text{sm4}, \beta \text{m4}\}$$

2.4. Feature selection

Selecting relevant features is an important task in machine learning process to obtain the highest classification performance. It simplifies the model for easier interpretation, reduces dimensionality of feature vectors, shortens training time, and reduces computational complexity (Mohanty et al., 2018). The feature selection technique removes redundant or irrelevant features from the dataset without much information loss. We have used two selection approaches based on particle swarm optimization (PSO) search and Chi-square test approach (Bing et al., 2013; Liu & Setionu, 1995) to select the optimum performing method.

2.5. Classification

2.5.1. Random forests (RF) classifier

It is one of the effective machine learning classifier proposed by Breiman (2001). The classification tree in RF is built by selecting features from random samples to obtain a class label. The structural network of the RF classifier is presented in Fig. 2. In the RF classifier, the best features are selected by Gini index, which is then used to build the binary tree.

The RF algorithm for classification and regression states as follows:

- Total number of training instances is P and the number of attributes is Q in the classifiers.
- Select the best discriminate attribute from the P instances.
- A training set for this tree is selected from N number of training cases, and the errors are estimated from rest of the cases by predicting their classes.
- Then randomly choose m variables for each node for decision and calculate the best split from m variables in the training set.
- The tree is moved down to assign the training label at the terminal node for predicting a new sample. The process is iterated over all trees and the prediction output of the forest is done by averaging the values of all trees.

The margin functions of the classifier using X, Y distribution random vectors are:

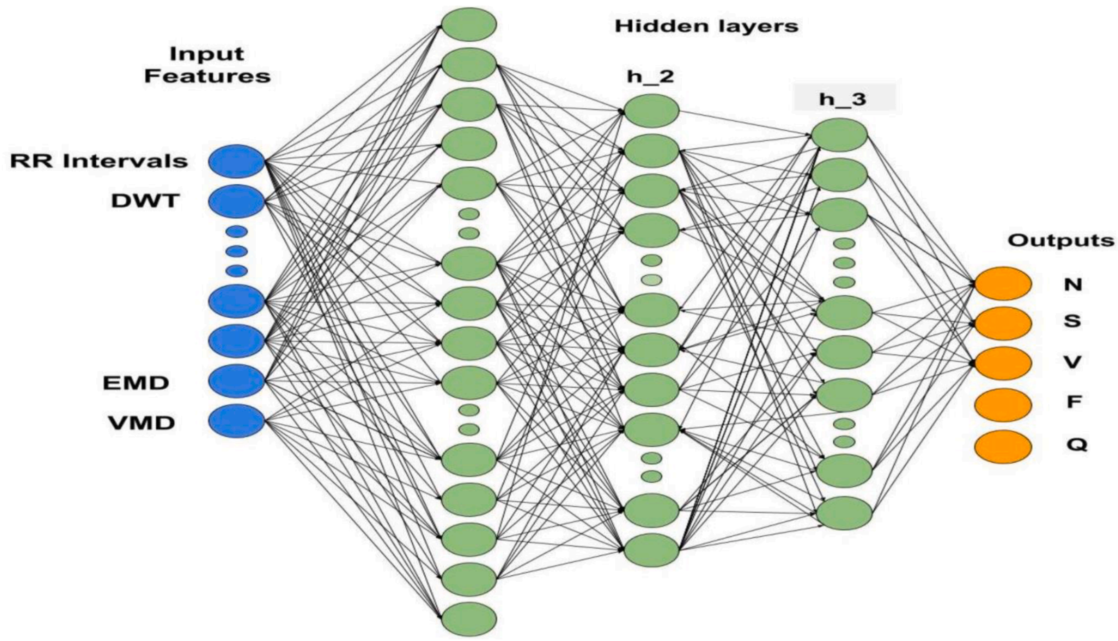

Fig. 3. Proposed DNN architecture used for arrhythmia detection.

$$mg(X,Y) = av_k(h_k(X) = Y) - \max_{j \neq Y} av_k I(h_k(X) = j) \tag{12}$$

where $I(.)$ is the indicator function, $h_k = [h_1(x),\ h_2(x), \ldots\ldots\ldots, h_k(x)]$ are the ensemble classifiers, $X,\ Y$ are the random vectors and mg is the margins. The generalization error of the classifier is defined as:

$$PE^* = P_{X,Y}(mg(X,Y) < 0) \tag{13}$$

The subscript X, Y indicates the probability over X, Y space. When the number of trees increases, the generalization error converges to:

$$P_{X,Y}\left(P \ominus (h(X,\ominus) = Y) - \max_{j \neq Y} P_{\ominus}(h(X,\ominus) = j) < 0\right) \tag{14}$$

Due to converges, the RF does not over-fit even when a greater number of trees are added.

The mean standard generalization error for the predictor $h(X)$ is:

$$E_{X,Y}(Y - h(X))^2 \tag{15}$$

When the number of trees in the forest goes to infinity then:

$$E_{X,Y}(Y - av_k h(X, \ominus_k))^2 \rightarrow E_{X,Y}(Y - E_{\ominus} h(X,\ominus))^2 \tag{16}$$

for all $\ominus$, $EY = E_X h(X, \ominus)$ *the* generalization error is given by

$$PE^*(forest) \le \overline{\rho} PE^*(tree) \tag{17}$$

where $\overline{\rho}$ is the weight correction between the residuals $Y - E_{\ominus} h(X,\ominus)$ and $Y - E_{\ominus} h(X,\ominus')$ where $\ominus$ and $\ominus'$ are independent factors.

Since a forest averages the predictions of a set of m trees with individual weight functions W_j , its predictions are given by

$$\widehat{y} = \frac{1}{m} \sum_{i=1}^{n} \frac{1}{m} \left(\sum_{j=1}^{m} W_j(x_i, x') \right) y_i \tag{18}$$

2.5.2. *Deep neural network model*

The structure of DNN model is modified to have more than two hidden layers (Jurgen, 2015). Basically, it follows the feedforward networks to transfer data from the input layer to the output layer. Initially it creates a map of virtual neurons and assigns randomly with some weights which are multiplied and return values between 0 and 1 at the output. The weights are adjusted themselves for better reorganization of

Table 1
List of features extracted from the various coefficients of different transformation techniques.

Features	Description	Features	Description	Features	Description
Q_{int}	QRS interval	σ_{D3}	Standard deviation of D_3	β_{I3}	Skewness of imf_3
P_{int}	PR interval feature	$\hat{}_{D4}$	Minimum value of D_4	μ_{I4}	Mean of imf_4
RR_i	Pre RR interval	$\vee_{D4}$	Maximum value of D_4	s_{I4}	Variance of imf_4
$RR_{(i+1)}$	Post RR interval	μ_{D4}	Mean of D_4	β_{I4}	Skewness of imf_4
RR_a	RR average	σ_{D4}	Standard deviation of D_4	μ_{m1}	Mean of $mode_1$
RR_l	RR local average	$\hat{}_{A4}$	Minimum value of A_4	s_{m1}	Variance of $mode_1$
$\hat{}_{D1}$	Minimum value of D_1	$\vee_{A4}$	Maximum value of A_4	β_{m1}	Skewness of $mode_1$
$\vee_{D1}$	Maximum value of D_1	μ_{A4}	Mean of A_4	μ_{m2}	Mean of $mode_2$
μ_{D1}	Mean of D_1	σ_{A4}	Standard deviation of A_4	s_{m2}	Variance of $mode_2$
σ_{D1}	Standard deviation of D_1	μ_{I1}	Mean of imf_1	β_{m2}	Skewness of $mode_2$
$\hat{}_{D2}$	Minimum value of D_2	s_{I1}`	Variance of imf_1	μ_{m3}	Mean of $mode_3$
$\vee_{D2}$	Maximum value of D_2	β_{I1}	Skewness of imf_1	s_{m3}	Variance of $mode_3$
μ_{D2}	Mean of D_2	μ_{I2}	Mean of imf_2	β_{m3}	Skewness of $mode_3$
σ_{D2}	Standard deviation of D_2	S_{i2}	Variance of imf_2	μ_{m4}	Mean of $mode_4$
$\hat{}_{D3}$	Minimum value of D_3	β_{I2}	Skewness of imf_2	s_{m4}	Variance of $mode_4$
$\vee_{D3}$	Maximum value of D_3	μ_{I3}	Mean of imf_3	β_{m4}	Skewness of $mode_4$
μ_{D3}	Mean of D_3	s_{I3}	Variance of imf_3		

Table 2
Summary of selected features obtained using Chi-square test and PSO search feature selection methods.

Chi-square test Feature weightage	Rank	Feature name	Feature weightage	Rank	Feature name	PSO search Feature weightage	Rank	Feature name	Feature weightage	Rank	Feature name
26,287.42	1	μ_{A4}	12,695.96	26	β_{I4}	0.491	1	μ_{A4}	0.124	26	v_{D4}
26,287.34	2	s_{m1}	12,655.56	27	RR_a	0.491	2	s_{m1}	0.124	27	μ_{I4}
23,951.62	3	β_{I1}	12,655.48	28	s_{m2}	0.445	3	s_{m3}	0.123	28	Q_{int}
23,468.25	4	μ_{m2}	12,655.47	29	μ_{m4}	0.445	4	RR_i	0.116	29	μ_{D2}
23,468.15	5	μ_{I1}	9970.99	30	μ_{D4}	0.435	5	σ_{D1}	0.112	30	β_{m1}
22,939.84	6	$s_{I1`}$	9970.88	31	μ_{I4}	0.420	6	β_{I1}	0.112	31	σ_{A4}
20,645.69	7	v_{A4}	9484.98	32	RR_l	0.325	7	μ_{m1}	0.109	32	$RR_{(i+1)}$
20,645.68	8	μ_{m1}	9484.61	33	β_{m2}	0.325	8	v_{A4}	0.109	33	β_{m3}
20,009.48	9	RR_i	9484.57	34	s_{m4}	0.322	9	$\hat{}_{D2}$	0.108	34	v_{D3}
20,009.41	10	s_{m3}	8081.67	35	μ_{D3}	0.232	10	β_{m2}	0.108	35	s_{I2}
19,417.46	11	σ_{D2}	8080.67	36	β_{I2}	0.232	11	RR_l	0.103	36	$\hat{}_{D1}$
19,354.10	12	σ_{D1}	7913.91	37	s_{I3}	0.232	12	s_{m4}	0.103	37	μ_{m3}
18,781.09	13	σ_{A4}	7913.80	38	$\hat{}_{D4}$	0.204	13	$\hat{}_{A4}$	0.103	38	β_{m4}
18,781.05	14	β_{m1}	6655.16	39	P_{int}	0.204	14	β_{I4}	0.103	39	s_{I3}
17,635.80	15	μ_{D2}	5813.69	40	s_{I2}	0.175	15	v_{D1}	0.103	40	$\hat{}_{D4}$
16,281.75	16	μ_{D1}	5813.61	41	v_{D3}	0.159	16	σ_{D3}	0.099	41	μ_{I1}
15,103.49	17	$\hat{}_{D2}$	5311.99	42	σ_{D3}	0.159	17	μ_{I3}	0.099	42	μ_{m2}
14,862.62	18	$RR_{(i+1)}$	5311.94	43	μ_{I3}	0.152	18	μ_{D3}	0.082	43	σ_{D4}
14,862.57	19	β_{m3}	4989.94	44	s_{I4}	0.152	19	β_{I2}	0.082	44	s_{I4}
14,268.86	20	v_{D2}	4988.94	45	σ_{D4}	0.148	20	P_{int}	0.078	45	μ_{D1}
14,244.96	21	$\hat{}_{D1}$	4791.96	46	v_{D4}	0.141	21	s_{m2}	0.077	46	$\hat{}_{D3}$
14,244.87	22	β_{m4}	4790.96	47	β_{I3}	0.141	22	RR_a	0.077	47	μ_{I2}
14,244.86	23	μ_{m3}	4447.89	48	Q_{int}	0.141	23	μ_{m4}	0.065	48	μ_{I4}
13,485.30	24	v_{D1}	3320.92	49	$\hat{}_{D3}$	0.136	24	σ_{D2}	0.065	49	μ_{D4}
12,695.99	25	$\hat{}_{A4}$	3319.92	50	μ_{I2}	0.131	25	v_{D2}	0.043	50	$s_{I1`}$

Table 3
Summary of performance obtained using two feature selection methods (Chi-square test and PSO search) with RF classifier.

Fold No.	Chi-square test Se (%)	Sp (%)	Pp (%)	Acc (%)	Comp. time (s)	PSO search Se (%)	Sp (%)	Pp (%)	Acc (%)	Comp. time (s)
2	97.33	99.35	96.12	98.91	0.14	95.01	97.32	95.12	97.07	0.12
3	97.53	99.45	96.83	99.09	0.16	95.20	97.45	95.33	97.10	0.11
4	97.84	99.50	97.16	99.08	0.14	95.48	97.52	95.29	97.28	0.11
5	98.29	99.50	97.13	99.11	0.13	95.97	97.71	95.07	97.51	0.13
6	98.36	99.49	96.90	99.12	0.13	96.12	98.98	96.09	98.33	0.11
7	98.58	99.57	97.64	99.15	0.15	97.24	99.05	97.32	98.76	0.11
8	98.49	99.56	97.69	99.28	0.16	97.02	99.15	97.12	98.21	0.11
9	98.89	99.55	97.74	99.46	0.14	97.11	99.10	97.20	98.03	0.11
10	99.27	99.71	97.88	**99.75**	0.13	97.14	99.21	97.22	98.01	0.11
Avg.	98.29	99.52	97.23	99.22	0.14	96.25	98.39	96.19	97.81	0.11

**Se: sensitivity; Sp: specificity; Acc: accuracy; Pp: positive predictivity.

patterns. For each of the possible configurations, we have calculated the classification accuracy using testing dataset. We have used ReLU (Rectified Linear Unit) activation function for our dataset which improved the performance by reducing computation cost. The highest classification performance is achieved with three hidden layers having 58, 29 and 46 neurons respectively as shown in Fig. 3.

3. Results

The wavelet transform was used to de-noise the ECG signal and detect R-peaks with a window of 260 samples to get the complete heart cycle. The heartbeat interval and RR interval features were extracted from each heart beats. Various features were extracted from the decomposed ECG signals with wavelet transform (db6) up-to 5th level, EMD (IMF_1 to IMF_4), VMD (mode-1 to mode-4) and formed a feature set. Table 1 shows the list of features extracted from each heartbeat and used as input to the RF classifier to classify the ECG beats. The Chi-square test and PSO search approach were used to select relevant features. Table 2 shows the summary of extracted features based on their weightage, and ranking with RF classifier. The 10-fold cross validation technique was used to develop the model. The performance parameters namely sensitivity (Se), specificity (Sp), positive predictivity (Pp) and accuracy (Acc) were used to evaluate the performance of the developed automated system.

The results of the classifier using Chi-square test and PSO search based feature selection techniques with 10-fold cross validation scheme is presented in Table 3. It can be observed that at fold-10, the Chi-square test-based method provided the best result whereas for the PSO search fold-7 obtained highest results. The overall results are better using Chi-square based ranking method. Fig. 4 shows the plot of average accuracy (%) versus number of folds for Chi-square test and PSO search feature selection methods with RF classifier. An average sensitivity, specificity and accuracy of 98.29%, 99.52%, and 99.22% with computation time of 0.14 s were achieved with Chi-squared test. An average sensitivity, specificity and accuracy of 96.25%, 98.39%, and 97.81% with computation time of 0.11 s were achieved using PSO based ranked features respectively. The highest accuracy of 99.75% was obtained using Chi-square test and 98.76% with PSO search based ranked features. These results indicates that the Chi-squared test ranked based feature is more effective than the PSO searched method for automated classification of ECG beats. To validate the DNN structure, accuracy, and loss curve is presented in Fig. 5 which shows with increasing in epochs the errors from training and testing are decreased. Fig. 6 is presented with the confusion matrix which is used to examine the model prediction on each class during the training and the testing process.

Our DNN model achieved a sensitivity of 99.22%, accuracy of

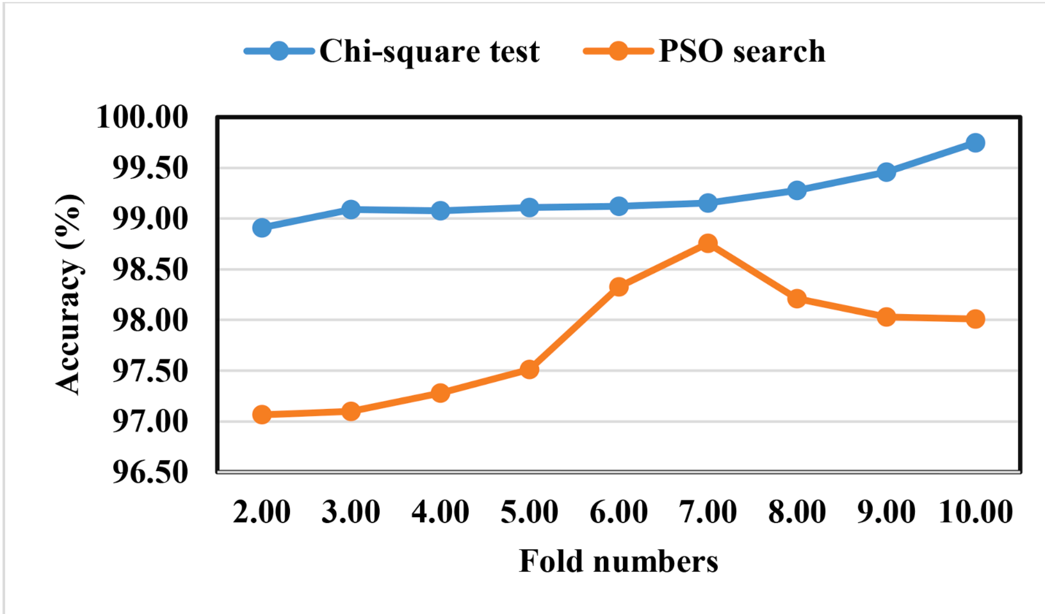

Fig. 4. Plot of average accuracy (%) versus number of folds for Chi-square test and PSO search feature selection methods with RF classifier.

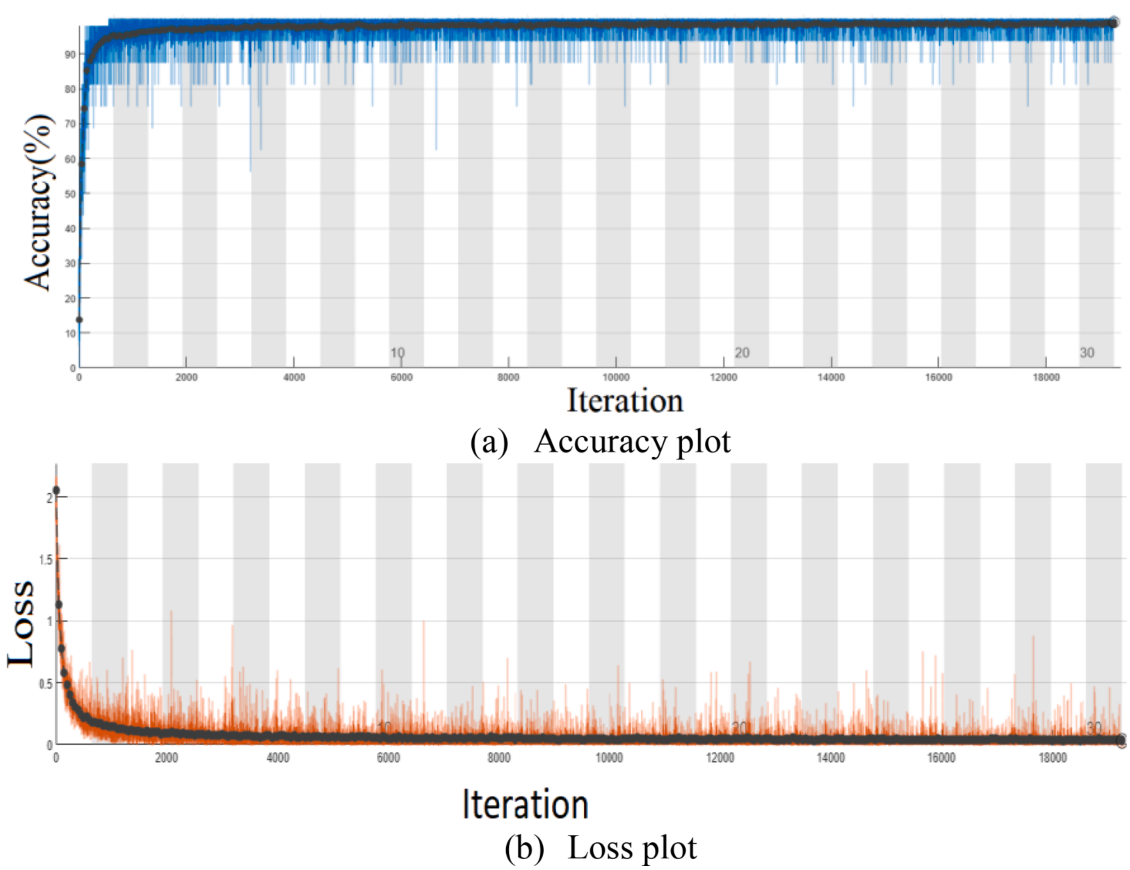

Fig. 5. Evaluation of Training and Testing of DNN classifier.

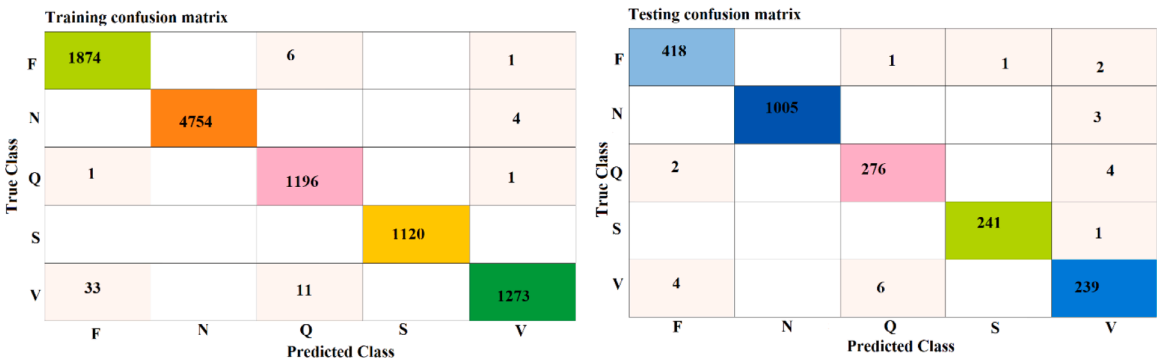

Fig. 6. Confusion matrix of Training and Testing process in DNN classifier.

Table 4
Comparison of performance obtained using classifiers (RF and DNN) with Chi-squared feature selection method.

Classifiers	Se (%)	Sp (%)	Acc (%)	Computation time (s)
Random Forest	98.29	99.52	99.22	0.14
DNN Model	99.22	99.74	99.75	0.043

99.75% and computation time of 0.43 s for the test set as shown in Table 4. Fig. 7 shows the comparison of performances between two classifiers (RF classifier and DNN) model.

4. Discussion

The proposed method combines the features obtained many transformation methods and used DNN to obtain high classification performance for arrhythmia detection. Our developed system is able to obtain highest performance due to the fusion of extracted features obtained from various coefficients of different transformations. The coefficients at various su-bands are able to capture minute variations present in the ECG signals and obtain highest classification performance in classifying the five ECG classes. Table 5 summarizes the different approach used by the researchers for automatic detection of arrhythmia using ECG signals obtained from the same MIT-BIH database. Our proposed DNN model achieved the best results with sensitivity, specificity, accuracy of 99.22%, 99.74%, and 99.53%, respectively using DNN classifier. Our developed model is ready to be tested with more data.

The advantages of our proposed system are as follows:

(1) Used the entire database to develop the model.
(2) Obtained the highest classification performance in classifying the five ECG classes (Table 5).
(3) Developed model is robust as it is developed using ten-fold cross validation technique.

Disadvantages of our developed model are given below:

1 Model classifies only five ECG classes.
2 Used ten-fold cross validation technique. Need to implement blind-fold cross validation in order to make the system robust and more accurate for clinical usage.

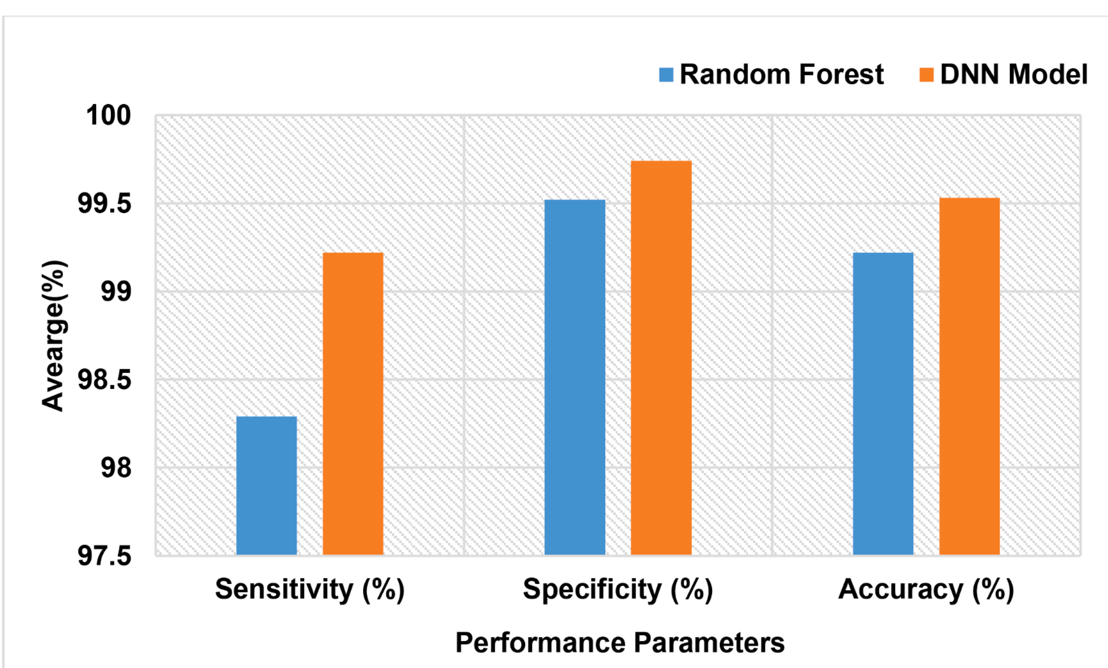

Fig. 7. Comparison of performances between two classifiers (RF and DNN).

Table 5
Summary of comparison of ECG beat classification using the same database.

Literature	Features	Classifier	Number of classes	Accuracy (%)
Shi et al. (2020)	ECGs segment	U-net model	5	97.32
Baloglu et al. (2019)	ECG signal	CNN algorithm	10	99
Yıldırım et al. (2018)	ECG segments	1D-CNN	17	91.33
Acharya et al. (2017a)	ECG segments	CNN algorithm	2	94.95
Yıldırım et al. (2018)	ECG segment	1D-CNN	17	91.33
Isin and Ozdalili (2017)	ECG images	Linear discriminant	3	92
Acharya et al. (2017b)	ECG images	CNN algorithm		95.2
Park et al. (2015)	Amplitude difference	Random forest	4	98.68
Park and Kang (2014)	QRS complex, P wave	Decision tree	2	94.6
Jiang and Kong (2007)	Hermit transfer coefficients, time interval	Block based neural network	2	96.6
Chazal and Relly (2006)	Morphology, heartbeat interval features	Linear discriminant	5	85.9
Li et al. (2022)	Hybrid features	1D CNN model	5	99
Kiani et al. (2019)	Hybrid features	Back Propagation Neural Network (BPN)	7	98.83
Wu et al. (2021)	Hybrid features	1D CNN	5	97.41
Proposed work	**Hybrid features**	**DNN model**	**5**	**99.75**

5. Conclusions

Early and accurate automated arrhythmia detection helps to provide timely treatment and helps to reduce the mortality rate significantly. A computer aided diagnosis system is proposed to detect the arrhythmias accurately using various decomposition techniques coupled with DNN. Our proposed method is able to detect accurately five arrhythmia classes with a sensitivity of 99.22%, specificity of 99.74%, accuracy of 99.53% using Chi Square test with DNN. In future, we intend to test our model with more diverse data and include a greater number of arrhythmia classes.

CRediT authorship contribution statement

Santanu Sahoo: Conceptualization, Methodology, Resources, Formal analysis, Writing – original draft, Writing – review & editing. **Pratyusa Dash:** Writing – original draft, Formal analysis, Writing – review & editing. **B.S.P. Mishra:** Conceptualization, Methodology, Resources, Writing – review & editing, Resources. **Sukanta Kumar Sabut:** Conceptualization, Methodology, Resources, Writing – original draft, Formal analysis, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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