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A Hybrid Feature Dimension Reduction and SVM for a Classification of Heart Rate Variability

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Abstract: Heart rate variability (HRV) is the variations in the time interval among heartbeats which indicates the status of the overall cardiac health. Reduced or abnormal HRV is related with an increased death risk. However, the classification of HRV is a challenging task because of the huge number of features processed during the diagnosis. In this research, an effective HRV classification is obtained using the hybrid feature dimension reduction (HFDR) technique along with the support vector machine (SVM) classifier. The HFDR is the combination of kernel principal component analysis (KPCA) and linear discriminant analysis (LDA) which is used to reduce the dimension of the overall feature vector. Three different feature extraction approaches such as continuous wavelet transform (CWT), autoregressive (AR) and spectrogram are used to understand the nonlinear and non-stationary features from the R peak obtained using hybrid R peak (HRP) detection. The reduction in feature dimension using HFDR is used to improve the classification of HRV. The electrocardiogram (ECG) signals from the MIT-BIH arrhythmia database of Physio.Net is used for analyzing the proposed HFDR-SVM. The HFDR-SVM method is evaluated using accuracy, precision, recall, sensitivity, specificity, and F-measure. The existing researches of forward back-propagation neural network (FFBPNN), weight-based ReliefF (WReliefF) with genetic algorithm (GA)-SVM, Alexnet-SVM and long short term memory with angle transform (LSTM-AT) are used for comparing the HFDR-SVM method. The accuracy of the HFDR-SVM is 99.86% that is higher than the FFBPNN, WReliefF-GA-SVM, Alexnet-SVM and LSTM-AT.

Keywords: Heart rate variability classification, Kernel principal component analysis, Linear discriminant analysis, Hybrid feature dimension reduction, Hybrid R peak detection, Support vector machine.

1. Introduction

Cardiovascular diseases (CVD) are considered one of the main reasons for mortality worldwide. The world health organization states that the CVD is number one cause of mortality, around 17.9 million (31%) people lost their lives because of CVD [1]. Different types of CVD are congenital, stroke, heart failure, arrhythmia, and coronary. However, Arrhythmia is the important reason for all CVD diseases increasing the rate of mortality. In the world, approximately 15–20% of all deaths are occurred because of Arrhythmia which is a major worldwide public health problem [2, 3]. In cardiac arrhythmia, the heart rate is irregular that is either extremely slow or extremely fast [4, 5]. The heart function's description and its condition exist in the ECG signal. ECG is non-invasive where a diagnostic tool is used to measure the heart's electrical activities. Further, the diagnostic tool is widely utilized for the clinical analysis of heart diseases [6-8]. But, the ECG signal is highly labor-intensive and ineffective for expert doctors while examining the signal [9].

The manual evaluation of ECG curves in a beat-by-beat manner is imprecise, tiresome, and time-consuming [10]. Hence, automatic analysis and classification of heart disease approaches are used for supporting cardiologists to make the best decisions for enhancing disease identification accuracy [11]

[12]. The ECG signals have various waves such as T-wave, P-wave, and QRS Complex along with numerous features, whereas the amount of extracted features is high when more electrodes are attached to various body parts [13]. Therefore, it is necessary to eliminate the features which aren't meaningful from the overall features. So, the dimensionality reduction approaches to play the main role in eliminating redundant features [14]. The selection of best features is used to achieve a higher recognition rate, simple classified calculation and optimal performance [15]. So, the dimensionality reduction is used in this research for achieving better HRV classification by using the nonlinear and non-stationary features of ECG.

The contributions are concise as follows:

- The HRP detection performed in this HFDR-SVM is used to acquire true R peaks and then the nonlinear and non-stationary features are extracted using CWT, AR and spectrogram approaches. The CWT, AR and spectrogram approaches are chosen because it provides good time and frequency resolution.
- An effective HRV classification is obtained using the hybrid feature dimension reduction technique along with an SVM classifier. The HFDR is the integration of KPCA and LDA which is utilized to minimize the dimension for the extracted features which used to enhance the classification accuracy. The reason for using HFDR is that the KPCA handles non-linear features while LDA handles the linear features.

The rest of the paper is arranged as follows: the existing research related to HRV classification is given in section 2. Section 3 delivers a detailed explanation of the HRV classification using HFDR and SVM. Section 4 delivers the outcomes of HFDR-SVM whereas the conclusion is presented in section 5.

2. Related work

Rajeshwari, and Kavitha, [16] presented the ensemble feature selection along with the deep neural network (DNN) to classify the arrhythmia. The developed ensemble feature selection was mainly depending on the feature's correlation for choosing the appropriate features from the finest solution of grasshopper, whale and grey wolf optimizations. For the chosen features, the correlation was computed and the features with higher correlation were chosen for classification using a deep neural network (DNN). The overfitting that occurred at the training was avoided by using the ReLU activation function in DNN. The interpretation of feature importance was difficult in the developed ensemble feature selection which led to degrading the classification.

Sharma [17] developed ECG sample classification into main arrhythmia classes based on the elimination of inherent noise by utilizing the discrete wavelet transformation. The QRS complex was important during the ECG signal. Hence, the amplitude and location of R-peaks have identified the QRS complex. Additionally, the QRS complex was optimized using the cuckoo search that was used to choose the appropriate feature set. Next, the hybrid model developed by using the SVM and Feed-FFBPNN were used to perform classification. The classification using FFBPNN was improved by developing the trained support vector using SVM. The developed SVM- FFBPNN required a huge amount of data for precise classification.

Yang, and Yan, [18] presented multidimensional feature extraction and selection methods to classify ECG arrhythmias. Initially, the shape features were extracted using the multi-interval symmetrized dot pattern (MSDP) approach. Further, the shape features from the MSDP were integrated with the RR interval features, time-frequency features and morphological features for creating a feature set. The average weight based ReliefF (WReliefF) was combined with the genetic algorithm (GA) and SVM to select an optimal feature subset. The SVM was used to classify the various classes of ECG beats according to the optimal feature subset, but SVM was not suitable to address the multi-class problems.

Çınar, and Tuncer, [19] developed the hybrid structure of Alexnet and SVM to classify the arrhythmia, normal sinus rhythm (NSR) and congestive heart failure (CHF) ECG signals. In Alexnet-SVM, the image properties were included in the last pooling layer whereas the SVM was replaced in this Alexnet instead of the softmax layer. The developed Alexnet-SVM does not need any feature extraction before applying the ECG signal. An effective dimension reduction was required to enhance the classification of ECG signals.

Mazaheri, and Khodadadi, [20] presented machine-learning approaches for classifying the normal rhythm from abnormal cardiac operations. At first, the segmentation of the ECG signal was performed followed by nonlinear indices, morphological characteristics and frequency domain features obtained for the ECG signal. Different algorithms such as differential evolutionary (DE), GA, particle swarm optimization (PSO) and non-dominated sorting GA (NSGA II) were used to perform the feature selection. The DE, GA and PSO were the single objective optimization which used to decrease only the cost function. Further, the multi-objective optimization namely NSGA II is used to simultaneously reduce the chosen feature number and cost function.

Kaya [21] presented the integration of long short term memory (LSTM) and angle transform (AT) for categorizing the ECG signals. The AT was used the adjacent signal's angular data on both sides of target signal for classifying the ECG signals. In this work, the LSTM was utilized in both unidirectionally and bidirectionally ways to classify the signals. The integration of LSTM and AT was used to achieve the higher success rates by using signal's histogram information. The LSTM-AT was processed with all histogram information obtained from ECG, it is required to use a dimensionality reduction for further improving the classification.

3. Proposed method

In this research, an effective HRV classification is obtained by using the hybrid feature dimension reduction technique along with an SVM classifier. The important processes of the proposed method are dataset acquisition, pre-processing, R peak detection, feature extraction, dimension reduction and classification. The HFDR is used to reduce the dimension of the extracted features which helps to improve the classification. The block diagram of the proposed method is given in Fig. 1.

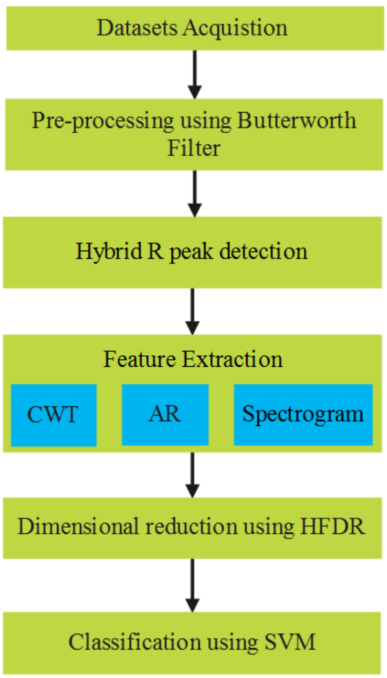

Figure. 1 Block diagram of the proposed method

3.1 Dataset acquisition

In this research, the ECG signals of NSR and CHF are taken for the classification of heart signals. The NSR and CHF signals are taken from the MIT-BIH Arrhythmia Database of Physio.Net [22].

3.2 Pre-processing using Butterworth filter

After acquiring the data, the filtering process is developed to remove the baseline wander noise that occurred during the ECG acquisition. This baseline wanders noise is occurred from the respiration and deceits between 0.15Hz and 0.3Hz. Here, the Butterworth filter of order 10 is used to remove the baseline wander of ECG. This Butterworth filter generated the Butterworth coefficients that were used to eliminate the noises. Further, denoising is performed using the wavelet transform [23].

3.3 Hybrid R peak detection

After pre-processing, the filtered ECG signal is given as input to the HRP for detecting the R peaks. The hybrid R peak (HRP) is a combination of protrusive *R* peak (PRP) and true R peak (TRP) [24] detections which used for an effective detection of *R* peak. Generally, the PRP is initialized, once the normalization is done in ECG signal. The protrusive upward *R* peak is discovered, when the value of peak exceeds or it is identical to value of upward threshold. Otherwise, the protrusive downward *R* peak is discovered, when the value of peak is lesser than downward threshold. Eq. (1) shows the logic of decision making.

$$PRP = \begin{cases} Upward\ R_{Peak}, & if\ peak(i) \geq Th_u \\ Downward\ R_{Peak}, & if\ peak(i) < Th_d \end{cases} \quad (1)$$

Where, Th_u and Th_d are value of current threshold for upward and downward *R* peak detections whereas this Th_u and Th_d are expressed in Eqs. (2) and (3) respectively

$$Th_u(i) = Th_u(i) + (\beta/2) \times (Th_u(i-1) - Th_u(i)) \quad (2)$$

$$Th_d(i) = Th_d(i) - (\beta/2) \times (Th_d(i-1) - Th_d(i)) \quad (3)$$

Where, $Th_u(i)$ & $Th_d(i)$ are updated threshold values, and $Th_u(i-1)$ & $Th_d(i-1)$ are previous threshold values; current peak amplitude is denoted as $peak(i)$ and constant factor is β that is expressed in Eq. (4).

$$\beta = \begin{cases} 0.25, & if\ R\ peak\ is\ missing \\ 0.125 & if\ T\ wave\ discovered\ as\ an\ R\ peak \\ 0 & else \end{cases} \quad (4)$$

The T wave of standard ECG is presented within $400\ ms$ after R peak in 1 cardiac cycle. Therefore, the peak is designated as PRP, if the time period crosses the $400\ ms$ after an earlier discovered R peak. Eq. (1) is used to discover the R peak and simultaneously intervals of RR peak are computed in PRP. The missing R peaks are determined by using the RR_{mean} of earlier discovered RR intervals. An interval of current RR that is higher than $1.5 \times RR_{mean}$ denotes the absence of R peak. Hence, the value of β is fixed as 0.25 and threshold is updated for discovering the lost R peak.

On the other hand, the discovered R peaks in the preprocessed ECG are not similar to the original ECG. The discovery of TRP is accomplished by using the position of PRP in the original ECG. A 30 ms window is considered to search the local maxima through both the right and left of PRP for upward R peak discovery. Similarly, the identical size of window is considered for downward R peak discovery. The downward and upward TRP are discovered in this stage. Moreover, the false R peak is eliminated by using the kurtosis coefficient in the detected R peaks. In general, kurtosis coefficient of T peak is always lesser than the R peak due to its former features. The false R peak is eliminated by comparing the kurtosis coefficients of R and T wave, therefore the β is fixed as 0.125 to update the threshold values.

3.4 Feature extraction

In this phase, the combination of CWT, AR and spectrogram [25] is used in this proposed approach for understanding non-stationary and nonlinear features. CWT offers best and reliable frequency resolution whereas AR provides good time-frequency resolution. For an each element of the ECG, a dominant and sufficient scale is evaluated during the feature extraction. Further, an effective calculation of frequency, time and power intensity data is obtained using the spectrogram. The process of feature extraction is detailed as follows:

3.4.1. CWT

In multiple scales, the non stationary signals are analyzed using CWT according to the analysis window for extracting the signal segments. The CWT of signal $y(t)$ by utilizing the wavelet functions $\psi_{\alpha,\beta}(t)$ expressed in Eq. (5).

$$CWT(\alpha,\beta) = \frac{1}{\sqrt{\alpha}}\int_{-\infty}^{\infty} y(t).\psi^*\left(\frac{t-\beta}{\alpha}\right)dt \quad (5)$$

Where, translation factor is denoted as β; scale factor is denoted as α and complex conjugate is represented using $*$. Further, the ψ^* value is translated and scaled complex conjugated mother wavelet function.

3.4.2. AR approach

The AR is chosen from time frequency analysis (TFA) approaches due to its better time frequency resolution. This AR is used to evaluate the model's order for the input to offer better outcomes. The order of model is essential because it denotes the amount of poles. An analysis of TR is provided both the TFA and power spectrum density. The process of AR is expressed in Eq. (6) for signal $y(t)$ with model order m and zero-mean white noise $\delta[t]$.

$$AR[t] = \sum_{j=1}^{m} \alpha_j y[t-m] + \delta[t] \quad (6)$$

3.4.3. Spectrogram approach

A time varying spectral density of input is provided by the spectrogram which depicts that the signal in time–frequency domain. This spectrogram is provided by a squared magnitude of the short time fourier transform (STFT) of signal which is expressed in Eq. (7).

$$Spectrogram(t,w) = |STFT(t,w)|^2 \quad (7)$$

Where, time in seconds is denoted as t and frequency in rad/sec is denoted as w.

The phase content and sinusoidal frequency of signal's sinusoidal frequency are computed using STFT whereas the signal is varied over time. STFT splits the signal as small sections and fourier transform is computed for each section of signal. Hence, the spectrogram denotes the time–frequency-intensity spectrum for a less time period.

The concatenated features from CWT, AR and spectrogram are expressed in Eq. (8).

$$x = \{CWT, AR, Spectrogram\} \quad (8)$$

3.5 Dimension reduction using HFDR

After extracting the features from the CWT, AR and spectrogram approaches, those features are concatenated and given as input to the HFDR. The HFDR is the integration of KPCA and LDA which is used to reduce the dimension for the extracted features. Here, the linear and non-linear features of the signals are handled by using LDA and KPCA respectively. The reduction in feature dimension is used to enhance the classification accuracy. In KPCA, a feature x is anticipated from the input space $\Re^n$ to higher dimension feature space $\Re^f$ using a nonlinear mapping function: $\Phi: \Re^n \to \Re^f, f > n$. The related eigenvalue problem for $\Re^f$ is expressed in Eq. (9).

$$C^{\Phi} w^{\Phi} = \lambda w^{\Phi} \tag{9}$$

Where, the covariance matrix is denoted as C^{Φ}; eigenvalue is denoted as λ and non-zero vector is represented as w^{Φ}. The solutions w^{Φ} with $\lambda \neq 0$ depends on the space extended by $\Phi(x_1), \Phi(x_2), \ldots, \Phi(x_N)$, where N is the cantered (i.e., zero mean) samples. The $N \times N$ matrix K is expressed in Eq. (10) and the KPCA issue is expressed in Eq. (11).

$$K_{ij} = \Phi(x_i).\Phi(x_j) \tag{10}$$

$$N\lambda K\alpha = K^2\alpha \equiv N\lambda\alpha \equiv K\alpha \tag{11}$$

Where, the column vector is denoted as α. Eqs. (10) and (11), consider that the anticipated samples $\Phi(x)$ are centered in $\Re^f$. The kernel function used by KPCA is the radial basis function.

Consider x is the test sample with projection of $\Phi(x)$ in $\Re^f$, therefore the $\Phi(x)$ over the eigenvector w^{Φ} is related to the Φ as shown in Eq. (12).

$$w^{\Phi}.\Phi(x) = \sum_{i=1}^{N} \alpha_i \big(\Phi(x_i)\Phi(x)\big) = \sum_{i=1}^{N} \alpha_i K(x_i, x) \tag{12}$$

On the other hand, the 1st $q (1 \leq q \leq N)$ non linear principal components are extracted using the kernel function which projected the samples to the higher dimensional space $\Re^f$. After performing KPCA based dimension reduction, each vector x_k is reduced to q kernel PCA coefficients y_k. To differentiate various roles of dissimilarities and to treat all features equally, the LDA is combined with the KPCA for improving the classification. The between-class and within class scatter matrix of LDA are expressed in Eqs. (13) and (14) respectively.

$$S_B = \sum_{i=1}^{C} N_i (\mu_i - \mu)^T \tag{13}$$

$$S_w = \sum_{i=1}^{C} \sum_{yk \in \omega_i} (y_k - \mu_i)(y_k - \mu_i) \tag{14}$$

Where, the mean vector of q-dimensional vectors for KPCA coefficients (y_k) is denoted as μ; the mean vector of y_k belongs to class ω_i is specified as μ_i; the amount of samples in class ω_i is represented as N_i. The projection matrix w_{LDA} is chosen by LDA in a manner that the proportion of the between-class scatter and the within-class scatter is denoted in Eq. (15).

$$W_{LDA} = \underset{w}{argmax} \frac{|w^T S_B w|}{|w^T S_w w|} \tag{15}$$

The final feature vectors from the hybrid KPCA and LDA are expressed in Eq. (16).

$$z_k = (w'_{LDA}) y_k \tag{16}$$

Therefore, the features from the HFDR are given as input to the SVM for classifying the HRV as NSR and CHF.

3.6 Classification using SVM

The feature set from the HFDR is given as input to the SVM [26] for performing the classification among NSR and CHF. SVM is generally a statistical learning approach that is used to solve the issues of regression and classification. The classification issue is solved by converting it into square optimization issue. Therefore, the SVM enhances the learning procedure and offers faster classifications. The SVM depends on the concept of defining the most appropriate hyperplane for differentiating between two classes that are defined as NSR and CHF.

4. Results and discussion

The outcomes of the proposed HRV identification using HFDR-SVM are provided in this section. The design and simulation of the HFDR-SVM method are done using the Labview software. Here, the system is operated with an i3 processor and 8GB RAM. The HFDR-SVM method is used to perform the classification of HRV into NSR and CHF. The dataset used to analyze the HFDR-SVM method is the MIT-BIH dataset where 80% is taken for training and 20% is taken for testing. The HFDR-SVM is examined by means of accuracy, precision, recall/sensitivity, specificity and F-measure are expressed in Eqs. (17) - (21). Further, the average computational time was also analyzed for evaluating the classification.

Table 1. Analysis of different classifiers without HFDR

Classifiers without HFDR	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)	Precision (%)
NN	88.04	87.30	89.85	87.79	88.28
KNN	90.17	89.11	91.48	90.01	90.93
SVM	95.85	94.86	93.58	93.83	92.83

Table 2. Analysis of different classifiers with HFDR

Classifiers with HFDR	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)	Precision (%)
NN	92.81	93.97	90.01	93.44	92.91
KNN	94.30	94.01	95.82	93.59	93.18
SVM	99.86	99.85	99.90	98.30	99.76

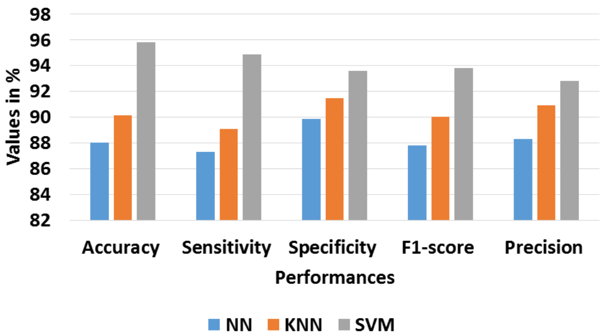

Figure. 2 Graphical illustration of different classifier's performance without HFDR

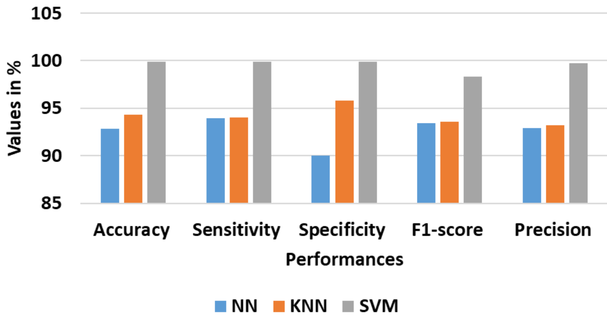

Figure. 3 Graphical illustration of different classifier's performance with HFDR

$$Accuracy = \frac{TP+TN}{TN+TP+FN+FP} \times 100 \quad (17)$$

$$Precision = \frac{TP}{TP+FP} \times 100 \quad (18)$$

$$Recall/Sensitivity = \frac{TP}{TP+FN} \times 100 \quad (19)$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \quad (20)$$

$$F - measure = \frac{2Precision \times Recall}{Precision+Recall} \times 100 \quad (21)$$

Where, TP is true positive; TN is true negative; FP is false positive and FN is a false negative.

4.1 Performance analysis of HFDR-SVM method

The performance of the HFDR-SVM method is analyzed in three different ways such as 1) different classifiers without HFDR, 2) different classifiers with HFDR and 3) different dimension reduction techniques. Table 1 and Fig. 2 show the performance analysis of different classifiers without the HFDR technique. The different classifiers used for the analysis are Neural Network (NN) and K Nearest Neighbor (KNN). From this analysis, it is known that the SVM provides better classification than the NN and KNN. The accuracy of SVM for HRV classification is 95.85%, whereas the NN obtains 88.04% and KNN obtains 90.17%. The SVM provides better performance because it is effective in handling high dimensional spaces and it provides clear margin separation among the classes of NSR and CHF.

The analysis of different classifiers with HFDR is provided in Table 2 and Fig. 3. Similar to the previous analysis, different classifiers such as NN and KNN are used for evaluating the HRV classification. This analysis shows that the classifiers with HFDR provide better classification when compared to the classifiers without HFDR. Specifically, the SVM with HFDR has higher accuracy of 99.86% than the SVM without HFDR. The accuracy of NN and KNN is 92.81% and 94.30% which are less than the SVM. The reason is that the HFDR reduces the dimension of the features and effective handling of high dimensional spaces using SVM helps to achieve a better classification.

Table 3 and Fig. 4 show the performance analysis of different dimension reduction techniques. The different dimension reduction techniques used for the analysis are KPCA, LDA and WReliefF-GA-SVM [18]. From the analysis, it is known that the HFDR (i.e., KPCA+LDA) provides better classification than the NN and KNN. The accuracy of HFDR-SVM for HRV classification is 99.86%, whereas the KPCA

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Table 3. Analysis of different dimension reduction techniques

Feature dimension reduction technique	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)	Precision (%)
KPCA	93.31	92.91	94.80	93.04	93.18
LDA	95.33	96.95	94.62	96.22	95.50
WReliefF-GA-SVM [18]	99.61	98.04	99.19	99.09	99.11
HFDR	99.86	99.85	99.90	98.30	99.76

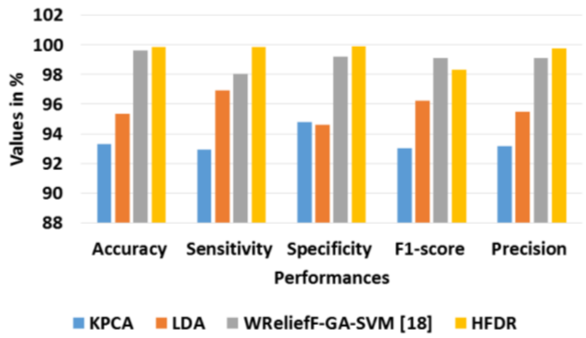

Figure. 4 Graphical illustration of different feature dimension techniques

obtains 93.31%, LDA obtains 95.33% and WReliefF-GA-SVM [18] obtains 99.61%. The HFDR achieves improved classification, because it used to handle both the linear and non-linear features of the ECG signal.

4.2 Comparative analysis

The existing methods such as FFBPNN [17], WReliefF-GA-SVM [18], Alexnet-SVM [19] and LSTM-AT [21] are used to evaluate the HFDR-SVM method. The FFBPNN [17] is implemented for HRV classification using the NSR and CHF signals from the MIT-BIH database to evaluate the HFDR-SVM. The comparative analysis of the HFDR-SVM method is shown in Table 4 and further graphical comparison for accuracy is shown in Fig. 5. This comparison shows that the HFDR-SVM method provides better HRV classification than the FFBPNN [17], WReliefF-GA-SVM [18], Alexnet-SVM [19] and LSTM-AT [21]. For example, the accuracy of HFDR-SVM is 99.86% where the FFBPNN [17] obtains 98.51%, WReliefF-GA-SVM [18] obtains 99.74%, Alexnet-SVM [19] obtains 97.84% and LSTM-AT [21] obtains 98.97%. The accuracy of HFDR-SVM is slightly increased than the WReliefF-GA-SVM [18]. The insufficient observations of WReliefF causes the overfitting issue which affects the sensitivity and specificity of WReliefF-GA-SVM [18]. But, the sensitivity and specificity of HFDR-SVM shows that the probability of precisely identifying the person with and without disease is high when compared to the WReliefF-GA-SVM [18]. The reason because of precise identification is handling both the nonlinear and linear features by KPCA and LDA in the feature reduction using HFDR. The following strategies are used to provide improved performances of HFDR-SVM: 1) The HRP based R-peak discovery is used to acquire only true R peaks where it eliminated the false R-peaks by considering the kurtosis coefficient, 2) The nonlinear and non-stationary feature extraction using CWT, AR and spectrogram is used to provide good time and frequency resolution for detected R peaks, and 3) The feature dimension reduction using HFDR is used to choose the optimal features that used to increase the classification of HRV.

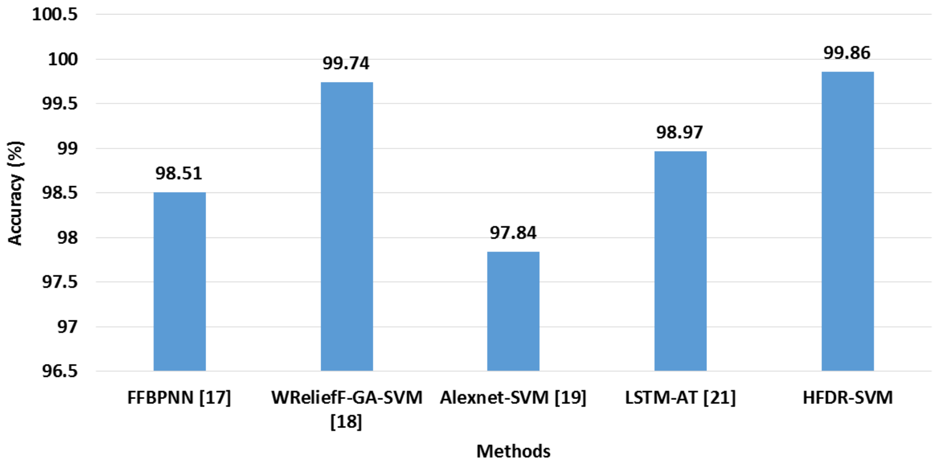

Figure. 5 Graphical comparison for accuracy

Table 4. Comparative analysis

Performances	FFBPNN [17]	WReliefF-GA-SVM [18]	Alexnet-SVM [19]	LSTM-AT [21]	HFDR-SVM
Accuracy (%)	98.51	99.74	97.84	98.97	99.86
Sensitivity (%)	98.37	99.42	98.33	99.42	99.85
Specificity (%)	98.06	99.83	NA	NA	99.90

5. Conclusion

In this research, an effective HRV classification is obtained by using dimension reduction along with HFDR. The butterworth filter is used in the pre-processing for removing the baseline wander noise from the ECG signal. The R peak detection is accomplished using the HRP approach where it uses the combination of PRP and TRP detection to acquire only true R peaks. The nonlinear and non-stationary features of detected R peak are extracted using CWT, AR and spectrogram approaches which used to obtain time-frequency resolution. The HFDR technique is used for reducing the feature dimension by considering both the linear and non-linear features, and the classification is done using SVM. The SVM provides better classification because it offered clear margin separation between the classes of NSR and CHF. From the results, it is known that the HFDR-SVM achieves better performances than the FFBPNN, WReliefF-GA-SVM, Alexnet-SVM and LSTM-AT. The accuracy of the HFDR-SVM is 99.86% that is higher than the FFBPNN, WReliefF-GA-SVM, Alexnet-SVM and LSTM-AT.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

For this research work all authors' have equally contributed in Conceptualization, methodology, validation, resources, writing—original draft preparation, writing—review and editing.

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