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Automated arrhythmia detection using novel hexadecimal local pattern and multilevel wavelet transform with ECG signals☆

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HIGHLIGHTS

- Classification 17 ECG classes is proposed.
- A novel hexadecimal ternary pattern is employed.
- Multilevel wavelet is used to extract features deeply.
- Obtained classification accuracy of 95.0%.
- Proposed method is computationally less intensive and fast.

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ABSTRACT

Electrocardiography (ECG) is widely used for arrhythmia detection nowadays. The machine learning methods with signal processing algorithms have been used for automated diagnosis of cardiac health using ECG signals. In this article, discrete wavelet transform (DWT) coupled with novel 1-dimensional hexadecimal local pattern (1D-HLP) technique are employed for automated detection of arrhythmia detection. The ECG signals of 10 s duration are subjected to DWT to decompose up to *five* levels. The 1D-HLP extracts 512 dimensional features from each level of the *five* levels of low pass filter. Then, these extracted features are concatenated to obtain $512 \times 6 = 3072$ dimensional feature set. These fused features are subjected to neighborhood component analysis (NCA) feature reduction technique to obtain 64, 128 and 256 features. Finally, these features are subjected to 1 nearest neighborhood (1NN) classifier for classification with 4 distance metrics namely city block, Euclidean, spearman and cosine. We have obtained a classification accuracy of 95.0% in classifying 17 arrhythmia classes using MIT-BIH Arrhythmia ECG dataset. Our results show that the proposed method is more superior than other already reported classical ensemble learning and deep learning methods for arrhythmia detection using ECG signals.

1. Introduction

In recent years, people are exposed to stress by the intense work environment and the rush of daily life [1–4]. The intense stress and work tempo increases the risk of arrhythmias or heart attacks. The cardiovascular diseases (CVDs) are the most serious health problems these days. Every year 17.9 million people die due to CVDs, which is 31% of all deaths in the world [5]. Hence CVDs are the world's leading global killer [6,7]. From the social point of view, the morbidity, mortality and cost of the treatment is gradually increasing. Also, there is shortage of cardiologists in many third world countries. Hence, it is very important to support the cardiologists through computer aided diagnosis. Such a solution reduces the risk of errors, facilitates the timely medical treatment to all and reduces the cost of diagnosis. So, development of computer aided diagnosis methods [8–13] can reduce the cost of CVDs diagnosis and treatment [8,14–17].

The state of art methods has many advantages but also few limits. They may not suitable for implementation in real-time applications as they are computationally intensive. Hence, we have developed an algorithm which can assist the cardiologists

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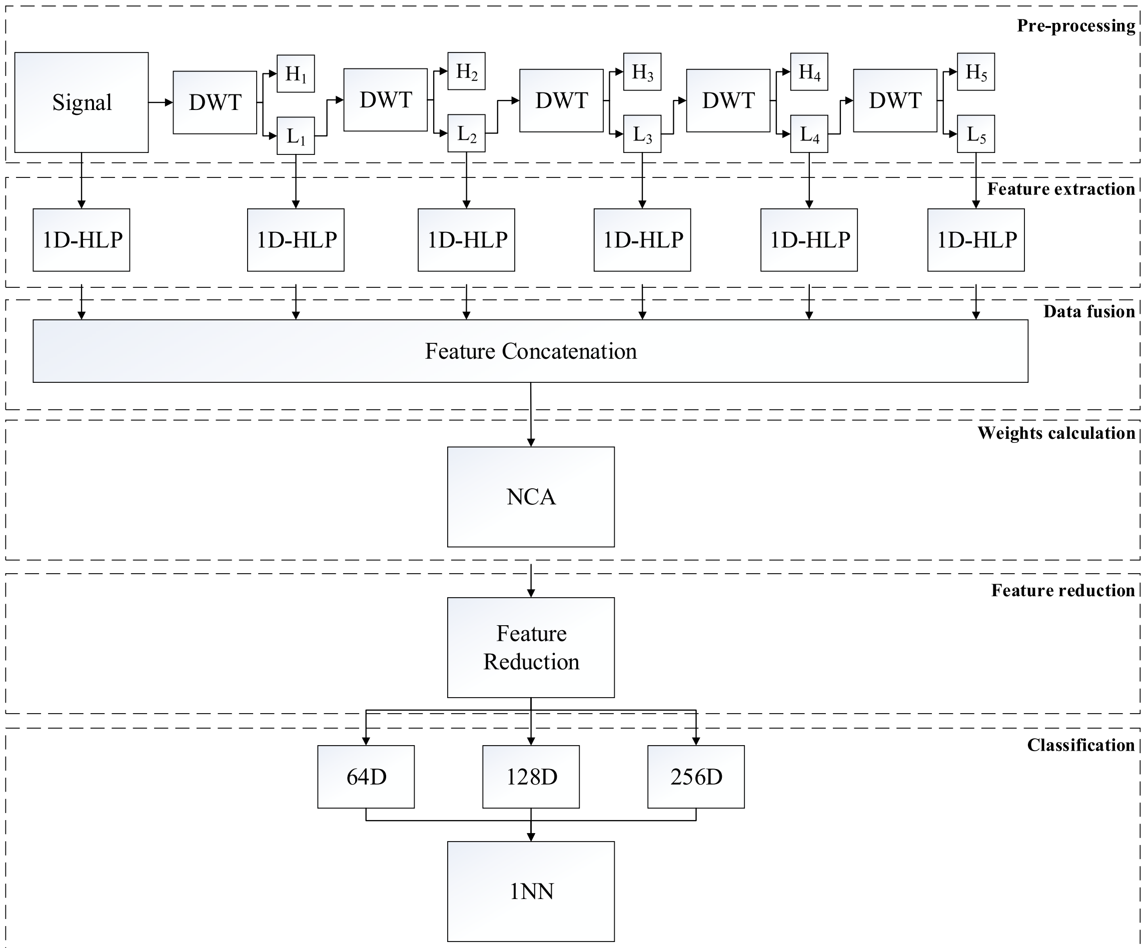


Fig. 1. The block diagram of the proposed method.

to detect the arrhythmia immediately and accurately. In order to achieve this, we have used discrete wavelet transform and local pattern algorithms.

The major contributions of the proposed method are listed in below.

- The ECG classification based on MIT-BIH Arrhythmia database is a challenging dataset as it consists of diverse classes of data with varied number of beats in each class. In this work we used, randomly selected 1000 ECG signal fragments of 10 s duration belonging to 17 classes [18]. To solve this problem, many classical machine learning [19], ensemble learning [20] and deep learning [21] based methods have been employed. These methods are computationally intensive. To achieve high success rate with low computational complexity, the multilevel discrete wavelet transform (DWT) and 1-dimensional hexadecimal local pattern (1D-HLP) based method is used. This method does not involve any ensemble and optimization method.
- The proposed method involves simple mathematical equations. Therefore, it can be employed in real-world environment.

The proposed method consists of pre-processing, feature extraction with 1D-HLP, feature concatenation, feature reduction using neighborhood component analysis (NCA) and classification phase. The general block diagram of the proposed method is shown in Fig. 1.

The DWT [22] is an effective signal transformation method. The ECG signal is decomposed in to five levels and L_1, L_2, L_3, L_4 and L_5 low frequency coefficients are obtained. To extract salient features from low frequency coefficient signals, 1D-HLP is used. This is a local pattern and it utilizes ternary function as the binary feature extraction function. To calculate threshold point of ternary function automatically, a standard deviation based formula is used. The NCA calculates feature weights. The calculated features weights are used to reduce the number of features to 64, 128 and 256.

1.1. Database

The electrocardiogram (ECG) is the most widely used base signal to detect the cardiac abnormalities accurately. Fig. 2 shows the samples of ECG signal fragments used in this work.

The ECG is defined as the recording of the electrical activity produced by the heart. An ECG record can identify the following conditions [7,23].

– Demand and structural heart diseases
– Heart involvement
– Pulmonary diseases
– Some drug effects
– Death.

The ECG is desirable in cases of chest pain, shortness of breath, palpitations and is widely used in the diagnosis and treatment of heart diseases [14,15]. The reasons for this widespread use are that, the ECG record can be applied to patients of all ages, cost is low, reproducibility is high, easy to evaluate and it is non-invasive.

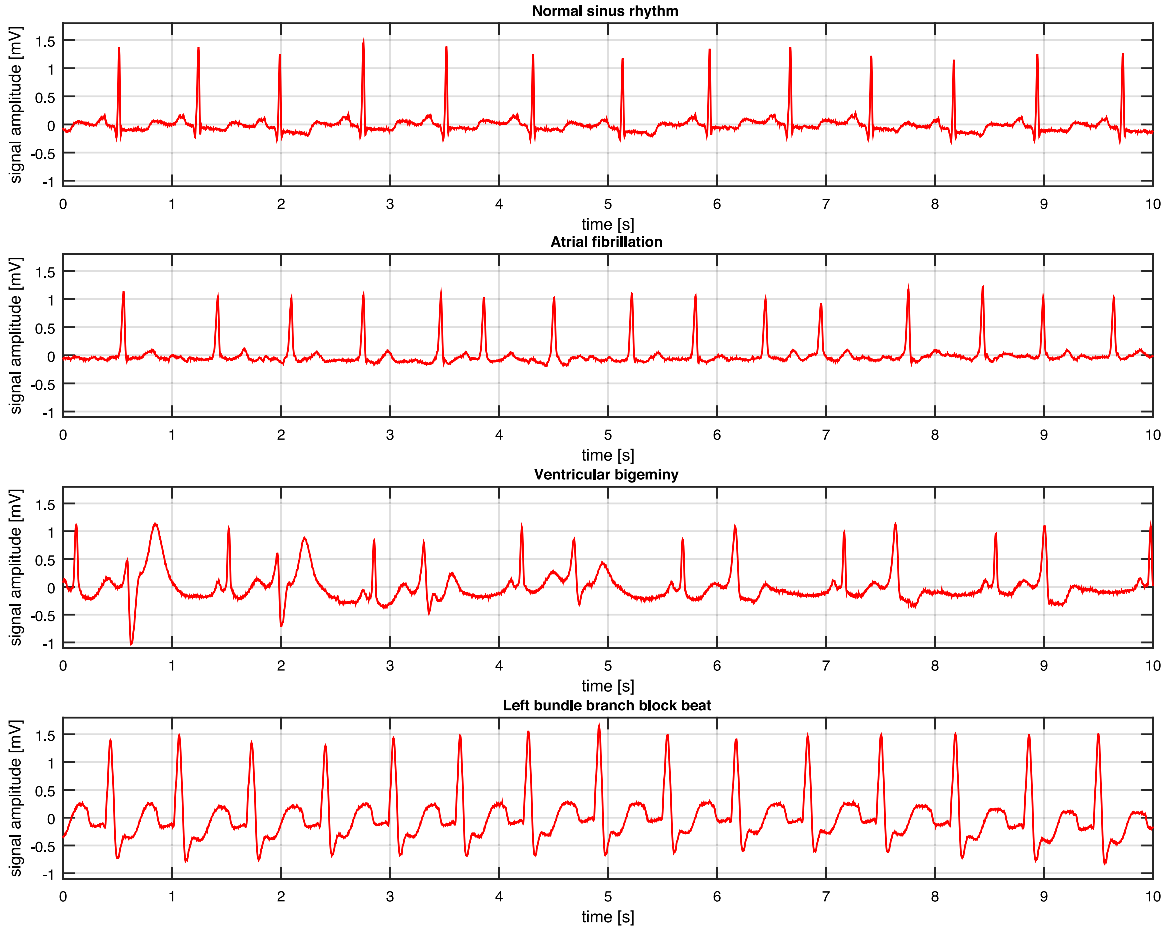


Fig. 2. A samples of used ECG signal fragments.

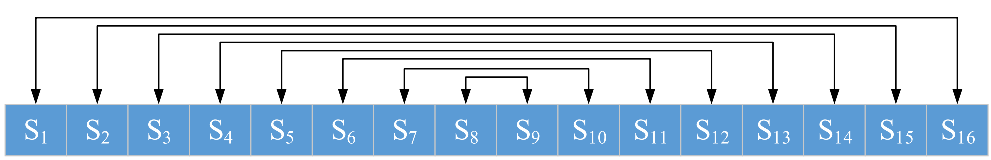


Fig. 3. Illustration of 1D-HLP.

In this study, the widely used [24] MIT-BIH Arrhythmia ECG signals dataset [18] was used to obtain the ECG signals of 17 classes. This dataset is a heterogeneous consisting of 1000 ECG signal fragments of 10 s duration obtained from 45 subjects belonging to 17 cardiac arrhythmias [25]. The details of the dataset are listed in Table 1.

The MIT-BIH dataset is one of the widely used database and widely used by the researchers to develop the best performing algorithm. Most of the best algorithms using ECG have been developed using this database as it provides a leeway to compare the performances.

2. Related work

Chazal et al. in [26] introduced algorithm for automated classification of five AAMI (Association for the Advancement of Medical Instrumentation) heartbeats classes (normal beat, ventricular ectopic beat (VEB), supraventricular ectopic beat (SVEB), fusion of a normal and a VEB, or unknown beat type). The MIT-BIH arrhythmia data set was used in the research, which was divided according to the inter-patient paradigm (subject-oriented validation scheme). This paper focused on the feature extraction based on RR-intervals, heartbeat intervals and ECG morphology. The authors have obtained an accuracy of 83%, using linear discriminant analysis (LDA). Zubair et al. in paper [27] presented ECG beat recognition system using convolutional neural networks (CNN). In the study MIT-BIH arrhythmia data set was used and five AAMI classes were recognized. An accuracy of 92.7% was achieved. Martis et al. in [28] proposed a solution for automatic detection of normal, atrial fibrillation (AF) and atrial flutter (AFL) ECG signals. They have compared four feature extraction methods namely: (a) independent components (ICs) of DWT coefficients, (b) principal components (PCs) of discrete wavelet transform (DWT) coefficients, (c) the ICs of DCT coefficients, and (d) PCs of discrete cosine transform (DCT) coefficients. They have employed three classifiers namely: K-nearest neighbor (KNN), decision tree (DT), and artificial neural network (ANN). They have reported the highest classification accuracy of 99.45% for DCT with ICA and kNN classifier. Elhaj et al. in article [29] described support

Table 1
Details of data used.

No	Class	Number of observations
1	Normal sinus rhythm	283
2	Atrial premature beat	66
3	Atrial flutter	20
4	Atrial fibrillation	135
5	Supraventricular tachyarrhythmia	13
6	Pre-excitation (WPW)	21
7	Premature ventricular contraction	133
8	Ventricular bigeminy	55
9	Ventricular trigemini	13
10	Ventricular tachycardia	10
11	Idioventricular rhythm	10
12	Ventricular flutter	10
13	Fusion of ventricular and normal beat	11
14	Left bundle branch block beat	103
15	Right bundle branch block beat	62
16	Second-degree heart block	10
17	Pacemaker rhythm	45

vector machine (SVM) and neural network algorithms with radial basis function for arrhythmia recognition and classification. In this paper, authors have connected linear and nonlinear features (principal component analysis (PCA) of DWT coefficients, cumulates, high order statistics, independent component analysis). Combined SVM with radial basis function (RBF) kernel has obtained 98.91% accuracy for the classification of five AAMI classes. Acharya et al. in work [30] used a novel deep learning method to classify heartbeats in ECG signals. Authors achieved an accuracy of 94.03% in the recognition of five AAMI classes using the 9-layer deep convolutional neural network (CNN). Bazi et al. in paper [31] used ECG wavelet features of QRS width and ECG morphology features. Authors have obtained an accuracy of 91.8% for domain transfer SVM (DTSVM), for five AAMI classes and subject-oriented validation scheme. Shu Lih Oh et al. in article [32] described a novel modified U-net model for automated arrhythmia classification. Authors designed auto encoder to recognition five classes. Authors have obtained accuracy equal to 97.32% using a 10-fold cross-validation (CV) method. Zhang and Luo in work [33] proposed multi-lead fused classification method. The ECG features adopted include: (a) amplitude morphology, (b) inter-beat and intra-beat intervals, (c) morphological distance, (d) area morphology, and (e) wavelet coefficients. Their developed solution has achieved an accuracy of 87.88%. Llamedo and Martinez in paper [34] introduced a simple heart beat classifier based on ECG feature models. Authors have considered features namely the ECG samples, RR series, and different scales of the wavelet transform. A floating feature selection algorithm obtained an accuracy equal to 93%. Yang et al. in work [35] developed a novel heartbeat classification solution. The main contribution was to used principal component analysis network (PCANet) for extraction of features. Linear support vector machine (SVM) obtained a score of 97.08% accuracy. Ye et al. proposed a new method for heartbeat recognition based on dynamic and morphological features [36] RR interval information, the wavelet transform and independent component analysis (ICA) were applied to feature extraction. The SVM method obtained the recognition accuracy 86.4% in diagnosis five AAMI classes, for subject-oriented scheme. Yildirim in article [37] described classification system for the recognition ECG signal heartbeats. He new algorithm is based on detection (wavelet transform) and segmentation of QRS complexes. Then the online sequential extreme learning machine method was applied to classifying the heartbeats. The developed model obtained an accuracy of 98.51% in the classification of five AAMI classes. Yildirim in paper [6] introduced a novel long-short term memory network (LSTM) and achieved an accuracy of 99.39%. Kalgotra et al. [38] described a method for automatic classification of five classes and reported an accuracy of 91,1% using binary relevance classifier. Their presented method can be applied in a commercial mobile device to monitoring the cardiac condition of patients. Hagiwara et al. (2018) [39] provided a review on the analysis methods used for the detection of atrial fibrillation (AF) using ECG signals. Li and Cui (2019) [40] presented machine learning techniques for ECG signal classification. Lannoy et al. (2012) [41] proposed an approach for classification of ECG signal using conditional random fields with SVM and LDA classifiers. Park et al. (2008) [42] used hermite basis function and higher order statistics (HOS). Ye et al. (2012) [43] employed combination of multi-class and specific two-class classifiers for ECG classification. Zhang et al. (2014) [44] presented a novel method for feature selection of heart beat classification. Mar et al. (2011) [45] proposed an optimization approach for feature selection. Saria and Martinez (2009) [46] developed a new method for ECG classification. Lin and Yang (2014) [47] presented a system for automatic classification of ECG signals using RR interval and morphological feature extraction method. Martis et al. (2013) [48] used HOS bispectrum and principal component analysis (PCA) for the classification arrhythmia using ECG signals. Huang et al. (2014) [49] proposed an approach using RR intervals and random projections. Martis et al. (2012) [50] presented an application for automated diagnosis of ECG signal using discrete wavelet transform (DWT) and PCA techniques. Same group [51] used discrete cosine transform (DCT) and PCA for ECG signal classification. Plawiak (2018) [52] presented a ECG classification system using genetic algorithm and SVM. Yıldırım et al. [53] proposed a convolutional neural network for the classification of 13, 15, 17 ECG classes with high classification accuracy.

3. The proposed ECG signals classification method

The proposed method (Fig. 1) consists of pre-processing, feature extraction with 1D-HLP, feature concatenation, feature reduction using neighborhood component analysis (NCA) and classification phase. The multilevel DWT [54] is used in the pre-processing phase to remove the noise and 5 levels of low-pass filters L_1, L_2, L_3, L_4 and L_5 are computed. To extract features, 1D-HLP is used and 512 $\times$ 6 dimensional features are extracted. These features are concatenated and 3072 dimensional feature set is obtained. In the feature reduction phase, weights of these features are calculated using NCA and 3072 dimensional features are reduced to 64 features using these weights. Finally, the extracted features are fed as inputs to the nearest neighborhood classifier

The steps of the proposed method are described in detail in the following sections.

3.1. Pre-processing

Step 1. Load ECG signal.

Step 2. Use 5 levels DWT and calculate L_1, L_2, L_3, L_4 and L_5. We used haar [55] wavelet function.

$$[L_1\ H_1] = DWT(S) \quad (1)$$

$$[L_2\ H_2] = DWT(L_1) \quad (2)$$

$$[L_3\ H_3] = DWT(L_2) \quad (3)$$

$$[L_4\ H_4] = DWT(L_3) \quad (4)$$

$$[L_5\ H_5] = DWT(L_4) \quad (5)$$

where $DWT(.)$ represents 1-dimensional DWT function with haar filter, S is ECG signals, L_1, L_2, L_3, L_4 and L_5 describes low pass filter coefficients. H_1, H_2, H_3, H_4 and H_5 indicate the high pass filter coefficients. The low-pass filter coefficients are the approximate coefficients. Therefore, these filters are used for feature extraction. In this step, pre-processing of the ECG signal is performed.

3.2. Feature extraction

Step 3. Extract features by using 1D-HLP. Steps of the 1D-HLP are given in the sub-steps.

Step 3.1. Divide signal into 16 dimensional overlapping blocks (Fig. 3).

Step 3.2. Calculate threshold value using Eq. (6).

$$t = \frac{SD\left(S\right)}{2} \tag{6}$$

where t is threshold value and $SD(.)$ is standard deviation function [56].

Step 3.3. Use ternary function to extract binary features. The mathematical description of ternary function is given in Eq. (7).

$$T\left(x, y\right) = \begin{cases} 1, & x - y > t \\ 0, & -t \leq x - y \leq t \\ -1, & x - y < -t \end{cases} \tag{7}$$

where $T\left(.,.\right)$ is ternary function, x and y are parameters of ternary function.

Step 3.4. Apply ternary function to block values.

$$T_i = T\left(S_i, S_{17-i}\right), \; i = \{1, 2, \ldots, 8\} \tag{8}$$

where T_i are ternary values of the block.

Step 3.5. Calculate the upper and lower bits.

$$lb_i = \begin{cases} 0, & T_i > -1 \\ 1, & T_i = -1 \end{cases} \tag{9}$$

$$ub_i = \begin{cases} 0, & T_i < 1 \\ 1, & T_i = 1 \end{cases} \tag{10}$$

where lb and ub describe upper and lower bits respectively.

Step 3.6. Calculate lower (l) and upper (u) values using lower and upper bits.

$$l = \sum_{i=1}^{8} lb_i \text{ x } 2^{8-i} \tag{11}$$

$$u = \sum_{i=1}^{8} ub_i \text{ x } 2^{8-i} \tag{12}$$

Step 3.7. Construct upper (US) and lower (LS) signals with dimension length(Signal)-15.

Step 3.8. Extract histogram of the US and LS.

Step 3.9. Concatenate upper and lower histograms to create feature set with dimension of 512.

The pseudo code of the 1D-HLP is also shown in Algorithm 1.

Algorithm 1. Pseudo code of the 1D-HLP.

Input: ECG signal S with length of k

Output: Feature of the 1D-HLP (feat) with size of 512.

for i= 1 to k-15 **do**
  $block = S(i{:}\, i + 15)$ // block construction
  $u(i) = 0; l(i) = 0;$
    for j=1 to 8 **do**
      if $T(block(i), block(17 - i) = 1$ **then**
        $u(i) = u(i) + u(i) \text{ x } 2^{8-j};$
      else if $T(block(i), block(17 - i) = 1$ **then**
        $l(i) = l(i) + l(i) \text{ x } 2^{8-j};$
      end if
    end for j
end for i
Extract histograms of u and l and obtain H_u and H_l
$feat = H_u \mid H_l$ // | is concatenation operator.

To better understand the proposed 1D-HLP, a numerical example is shown in Fig. 4.

Step 4. Extract features from ECG signal L_1, L_2, L_3, L_4, and L_5 using 1D-HLP.

3.3. Data fusion

Step 5. Concatenate features.

$$feat_C = feat_S \mid feat_{L_1} \mid feat_{L_2} \mid feat_{L_3} \mid feat_{L_4} \mid feat_{L_5} \tag{13}$$

where $feat_C$ and $feat_S$ are concatenated features and features of ECG signal respectively.

Step 6. Normalize the concatenated features.

$$feat_C = \frac{feat_C - \min(feat_C)}{\max\left(feat_C\right) - \min(feat_C)} \tag{14}$$

3.4. Weights calculation

Step 7. Perform NCA to calculate weights of the normalized features.

$$w = NCA(feat_C) \tag{15}$$

where w describe weights of the features with size of 3072.

Neighborhood component analysis (NCA): It learns the feature weighting vector by maximizing the expected classification accuracy with a normalization term. More importantly, the NCA does not lose any information in the process of dimensional reduction. It uses distance metrics to calculate feature weights (Eq. (15)). It is a supervised and non-parametric feature selection method. It calculates weights of the features and these weights are used to reduce features. The mathematical description of the proposed feature reduction method is given in Eq. (16) [57].

$$f\left(r\right) = \frac{\sum_{j=1}^{k} w(j) \text{ x } feat_c\left(j\right)}{\sum_{j=1}^{k} w(j)}, \; j = \{1, 2, \ldots, k\}, \; r = \{1, 2, \ldots, \frac{L}{k}\} \tag{16}$$

where f is reduced feature, $feat_c$ is concatenated features, L represents length of the concatenated features, i, j and r determine index.

3.5. Feature reduction

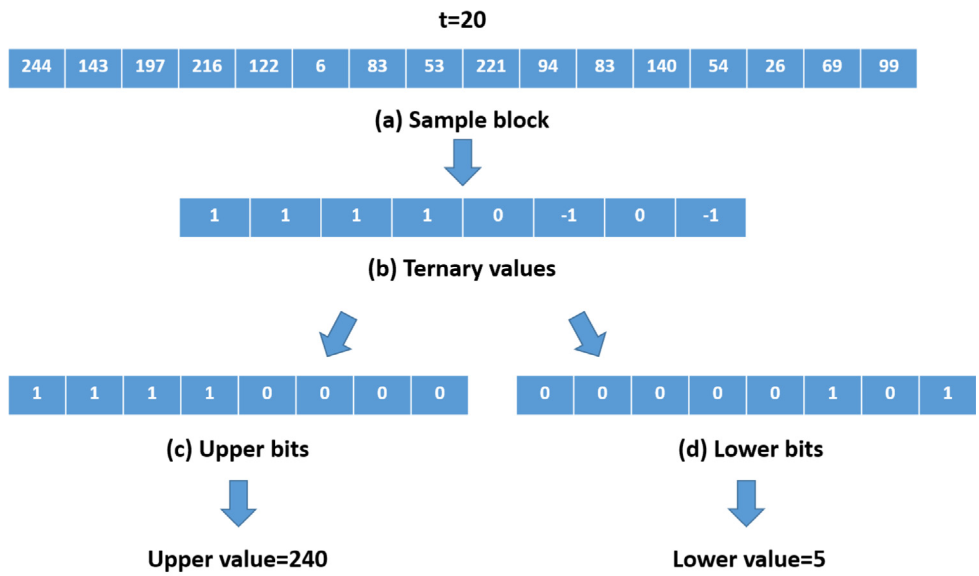
Step 8. Use Algorithm 2 to reduce features from 3072D to 64D, 128D and 256D.

Algorithm 2. Pseudo code of the NCA based feature reduction algorithm.

Input: Concatenated features $(feat_C)$ with dimension of 3072 and weights (w) of these features.

Output: Final features (f) with dimension of 64, 128 or 256.

$c = 1$; // c is counter.
for i= 1 to 3072 **step by** ts **do** // ts values are 48, 24 and 12 to reduce 64, 128 and 256 dimensional features
  $v_1 = 0; v_2 = 0;$
    for j=0 to ts-1 **do**
      $v_1 = v_1 + feat_c(i + j) \text{ x } w(i + j);$
      $v_2 = v_2 + w(i + j);$
    end for j
    $f(r) = \frac{v_1}{v_2}$
    $r = r + 1;$
end for j



(a)

$block_1$-$block_{16}$	244-99=145	145>20 → T_1 =1
$block_2$-$block_{15}$	143-69=74	74>20 → T_2 =1
$block_3$-$block_{14}$	197-26=171	171>20 → T_3 =1
$block_4$-$block_{13}$	216-54=162	162>20 → T_4 =1
$block_5$-$block_{12}$	122-140=-18	-20<-18<20 → T_5 =0
$block_6$-$block_{11}$	6-83=-77	-77<-20 → T_6 =-1
$block_7$-$block_{10}$	83-94=-11	-20<-18<20 → T_7 =0
$block_8$-$block_9$	53-221=-168	-168<-20 → T_8 =-1

(b)

Fig. 4. Illustration of 1D-HLP working with an example.

3.6. Classification

Step 9: Forward f to 1NN classifier.

1NN: 1NN is simplest version of the KNN classifier. In this classifier, k is selected as one. 1NN uses distance metrics such as Euclidean, City block, Spearman to perform classification [58].

4. Results

The proposed method is simulated using MATLAB 2018a and classification learner toolbox. The performance computer (PC) used for simulations has Windows 10.1 operating system. The tests are performed on a personal computer with 256 GB SDD hard disk, 16 GB RAM, intel i7-7700 CPU with 3.60 GHz on Windows 10.1 operating system.

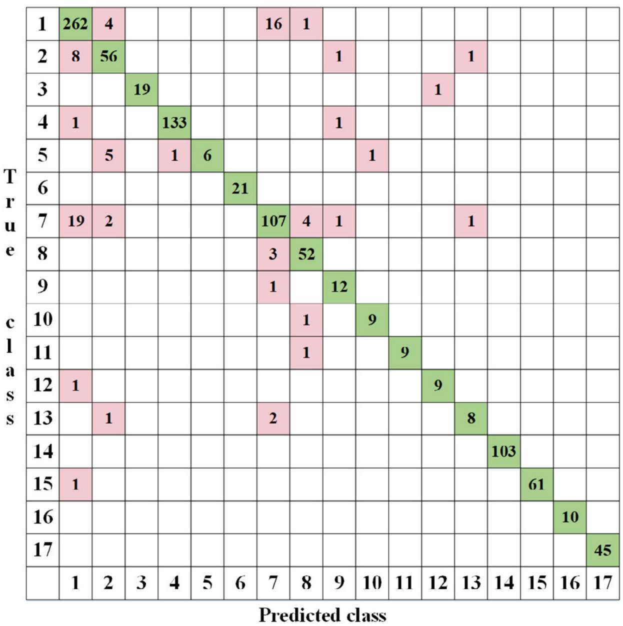
Table 2
The average execution time of the proposed method.

Feature extraction for single fragment	Classification of 1000 fragment using 1NN with 10-fold cross validation
23.0583 ms	0.8242 s

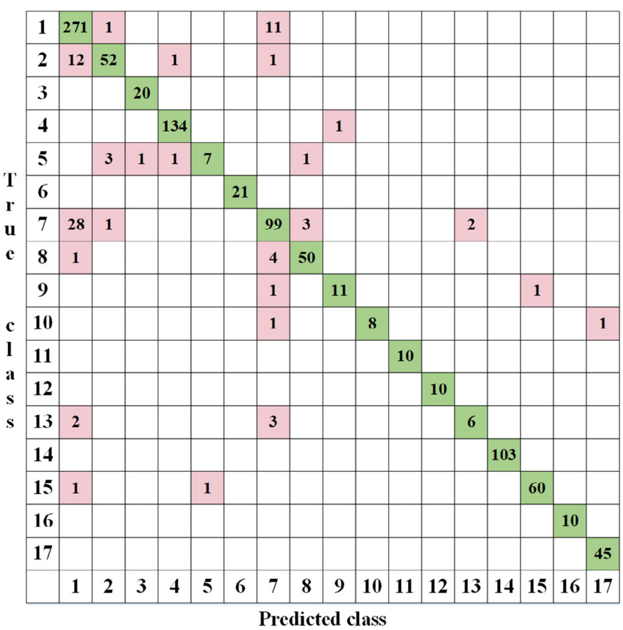
To better understand the proposed method, computational complexity and execution times of this method were calculated and the results are listed in Tables 2 and 3.

Tables 2 and 3 show that the proposed method takes shorter execution time.

Stratified 10-fold cross validation was performed to calculate accuracy rates. The mathematical description of the accuracy is

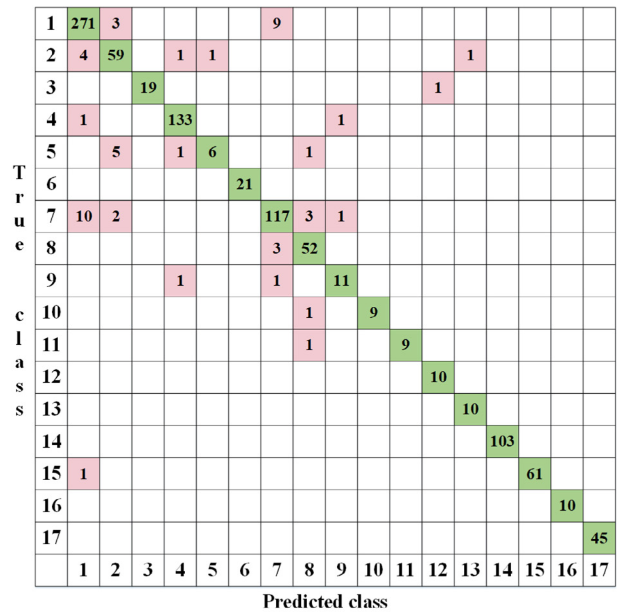


(a) Euclidean

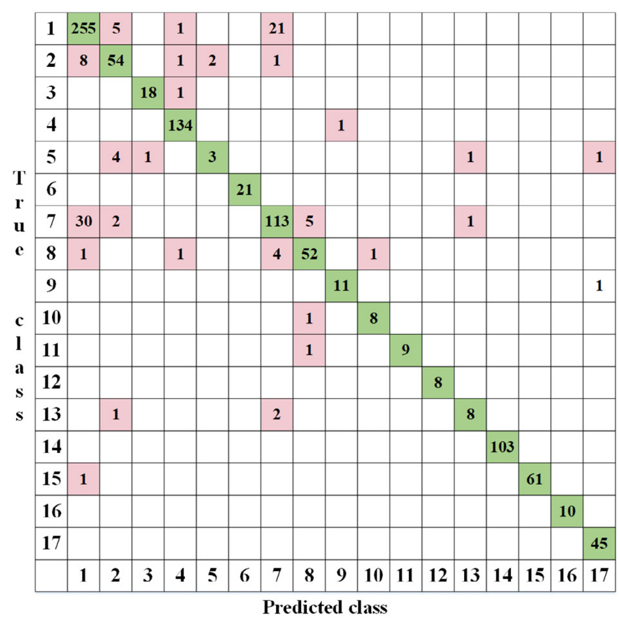


(b) Spearmen

Fig. 5. Confusion matrix obtained using 64 features using 1NN classifier with different distance metrics: (a) Euclidean, (b) Spearman, (c) city block, and (d) cosine.



(c) city block



(d) cosine.

Fig. 5. (*continued*).

Table 3
Space complexity of the proposed feature extraction method.

Steps of the proposed method	Cost
1: Apply 5 levels DWT with haar filter on the signal	$O\left(\sum_{i=1}^{5} \frac{n}{2^{i-1}}\right) = O\left(\frac{31n}{16}\right)$
2: Perform 1D-HLP to signals and sub-bands.	$O(n + \sum_{i=1}^{5} \frac{n}{2^{i-1}})$
3: Extract histograms	$O(512 \times 6) = O(3072)$
4: Concatenate histograms	$O(512 \times 6) = O(3072)$
5: Apply NCA	$O(512 \times 6) = O(3072)$
6: NCA based feature reduction	$O(512 \times 6) = O(3072)$
Total: $O\left(\frac{78n}{16} + 12288\right) \cong O(n)$	

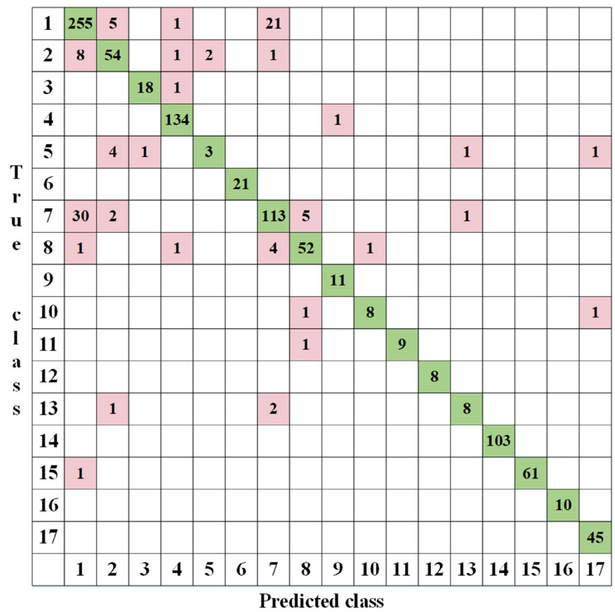
shown in Eq. (17) [59,60].

$$Acc = \frac{TP + FP}{TP + FP + TN + FN} \tag{17}$$

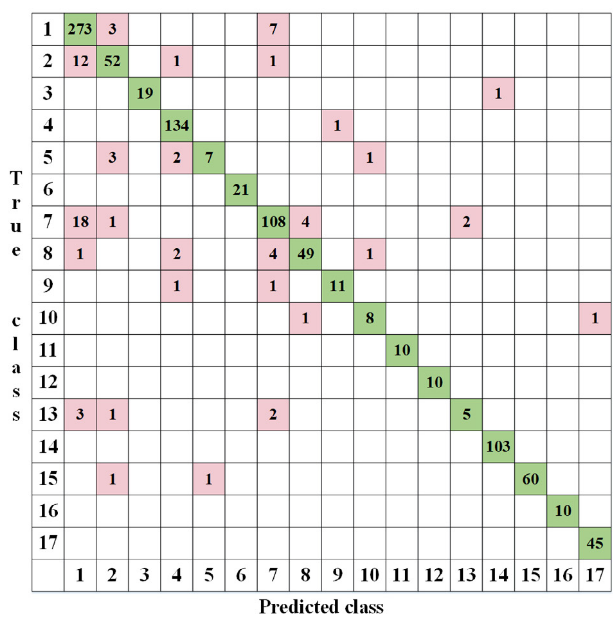
where Acc is accuracy, TP, FP, TN and FN are true positives, false positives, true negatives and false negatives respectively.

For classification, 1NN classifier was used with 4 distance metrics. These distances are Euclidean, Spearman, city block and cosine [61,62]. These distances were used to obtain numerical results. The mathematical description of these distances are given below.

$$E(x, y) = \sqrt{x^2 - y^2} \tag{18}$$

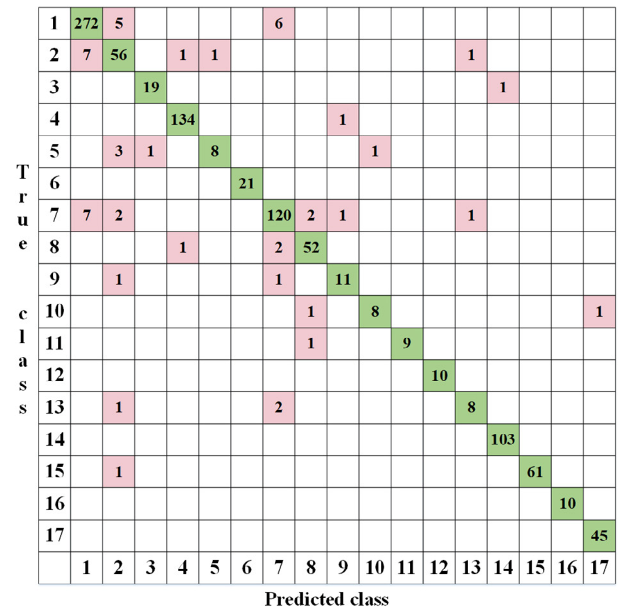


(a) Euclidean

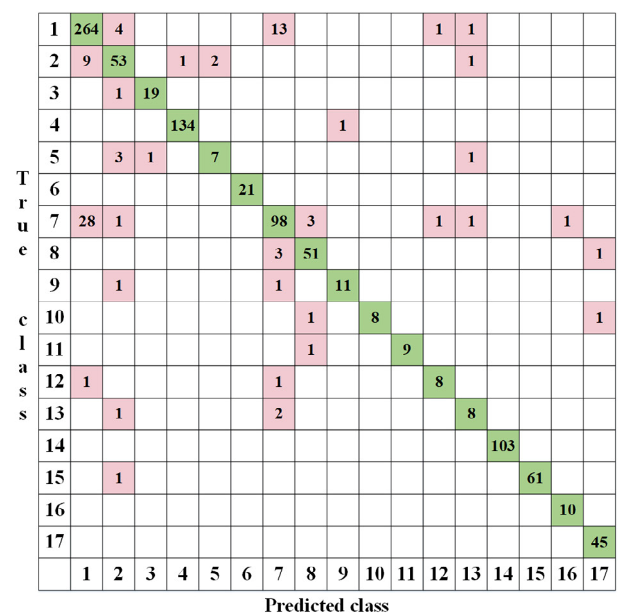


(b) Spearmen

Fig. 6. Confusion matrix obtained using 128 features using 1NN classifier with different distance metrics: (a) Euclidean, (b) Spearman, (c) city block, and (d) cosine.



(c) city block



(d) cosine.

Fig. 6. (*continued*).

$$Sp\,(x, y) = x^2 - y^2 \tag{19}$$

$$Cb\,(x, y) = |x - y| \tag{20}$$

$$Cos\,(x, y) = \frac{xy}{\|x\|\,\|y\|} \tag{21}$$

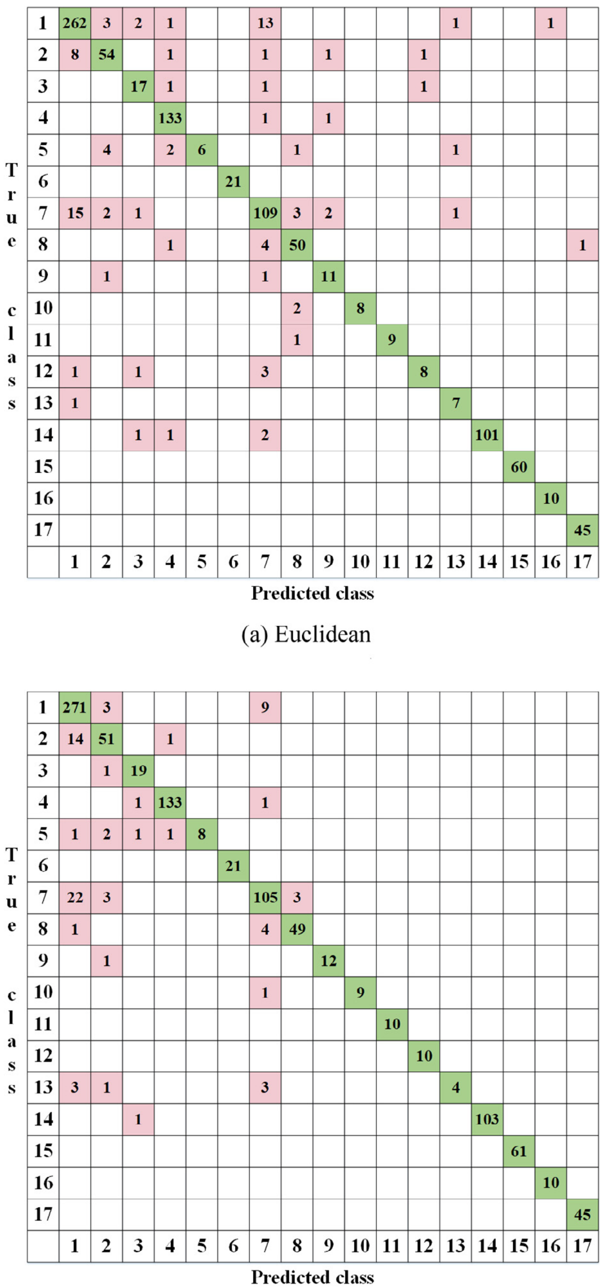
where x and y are input parameters of the distance metrics, $E\,(.)$, $Sp\,(.)$, $Cb(.)$ and $Cos(.)$ function describe Euclidean, Spearman, city block and cosine distances respectively.

The calculated confusion matrixes obtained using 64 features are shown in Fig. 5, 128 features are shown in Fig. 6, and 256 features are shown in Fig. 7.

It can be seen from Fig. 5 that, the accuracy rates are 92.2%, 91.7%, 94.6% and 91.2% for Euclidean, Spearman, city block and cosine distances respectively with 1NN classifier using 64 features.

It can see from Fig. 6 that, accuracy rates are 91.3%, 92.5%, 94.7% and 91.0% for Euclidean, Spearman, city block and cosine distances respectively with 1NN classifier using 128 features.

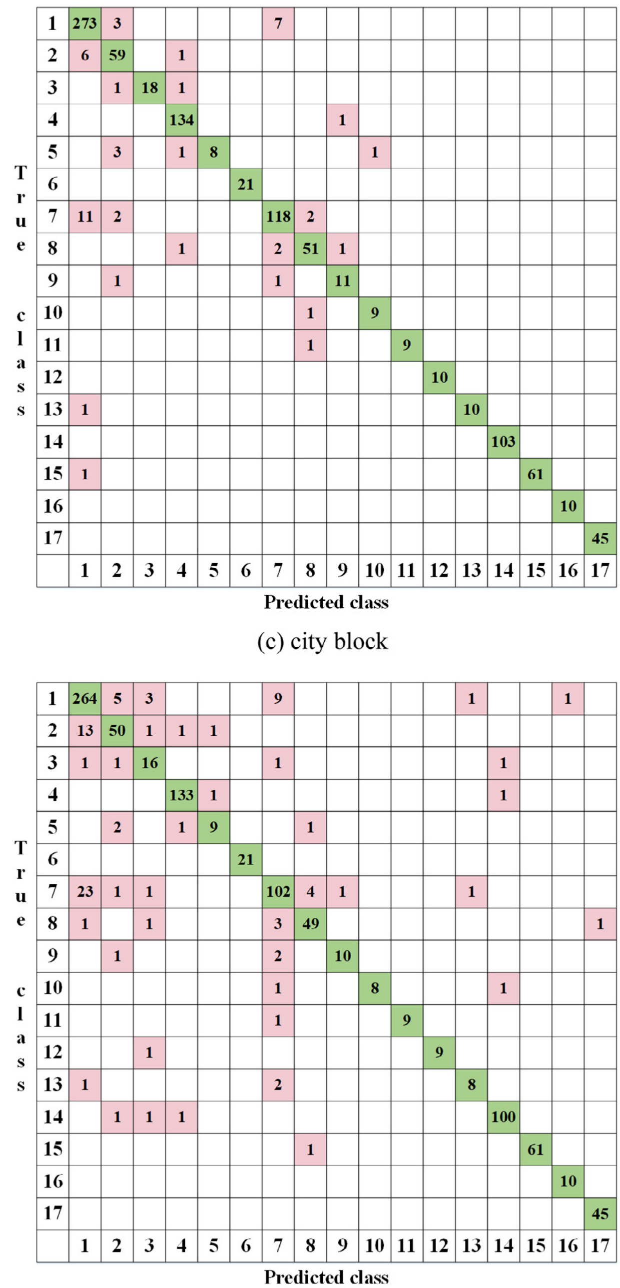
It can be seen from Fig. 7 that the accuracy rates are 91.1%, 92.1%, 95.0% and 90.4% Euclidean, Spearman, city block and cosine distances respectively with 1NN classifier using 256 features.



(a) Euclidean

(b) Spearmen

Fig. 7. Confusion matrix obtained for 256 features using 1NN classifier with different distance metrics: (a) Euclidean, (b) Spearman, (c) city block, and (d) cosine.



(c) city block

(d) cosine.

Fig. 7. (*continued*).

5. Discussion

In this paper, a novel 1D-HLP feature extraction method is employed. To reduce the number of features, NCA based data reduction algorithm is used. We have reduced the features to 64, 128 and 256 from the original feature set using NCA. The NCA gives good separation between the features. Hence, it has yielded high classification accuracy. Fig. 8 presents schematic diagram of feature values obtained after using NCA.

The box plot of feature values obtained after performing NCA for each class is shown in Fig. 9.

The boxplots shown above show the feature values for various ranked features. It shows the range of feature values. The blue boxes describe the difference between third and first quarters. The red stars represent the lower and upper bound values.

Also, the summary of the works conducted on automated classification of arrhythmia classes is shown in Table 4. Many machine learning methods using various nonlinear features have been proposed for classification of five types of arrhythmias [26,27,29–34,36,41–43,45–47,49,63]. Frequency components of the ECG signals coupled with evolutionary neural network using SVM classifier was used in [25]. Their proposed method yielded a classification accuracy of 90% for 17 classes. Same author in another study used genetic ensemble of SVM classifiers with frequency components of the ECG signals and classified the same 17 classes [52] The proposed method has obtained an accuracy

Table 4
Comparison of results obtained for 5 classes using MIT-BIH arrhythmia database.

Methods	Feature set	Classifier	Computational complexity	Accuracy (%)
De Lannoy et al. [41]	HBF, morphological, ECG-segments, HOS, RR intervals	Weighted CRF	O(n)	85.0
Park et al. [42]	HOS, HBF	Hierarchical SVM	O(n)	85.0
Ye et al. [43]	ICA, RR interval, Wavelet, PCA, Morphological	Combined SVM	O(n)	86.0
Zhang et al. [44]	ECG segments and intervals, morphological features, RR intervals	Combined SVM	O(n)	86.0
Zhang and Luo [33]	ECG segments and intervals, morphological features, RR intervals, wavelet coefficients	SVM	O(n)	87.0
Mar et al. [45]	Morphological, statistical features, Temporal Features, SFFS	MLP, Weighted LD	O(n)	89.0
Soria and Martinez [46]	Morphological features, RR Intervals, VCG, FFS	Weighted LD	O(n)	90.0
Bazi et al. [31]	Morphological, Wavelet	SVM, IWKLR, DTSVM	O(n)	93.0
Lin and Yang [47]	Normalized RR interval	Weighted LD	O(n)	93.0
Llamedo, J.P. Martínez [34]	VCG, SFFS, Wavelet	Weighted LD	O(n)	93.0
Martis et al. [48]	Higher Order Statistics (HOS), PCA	LS-SVM	O(n)	93.5
Huang et al. [49]	Random projection, Rrintervals	Ensemble of SVM	O(n)	94.0
Acharya et al. [30]	Raw data	CNN	$O(n^3)$	94.0
Oh et al. [32]	Raw data	U-net	$O(n^3)$	97.3
Oh et al. [63]	Raw data	Combination of CNN and LSTM	$O(n^3)$	98.1
Martis et al. [50]	Principal components of segmented ECG beats	LS-SVM with RBF kernel	O(n)	98.1
Martis et al. [64]	DWT, ICA	PNN	O(n)	99.3
Martis et al. [51]	DCT, PCA	PNN	O(n)	99.5
Yildirim et al. [65]	Deep CAE-LSTM	LSTM	$O(n^3)$	99.2
The proposed method with 64 features	5-levels DWT and 1D-HLP	1NN with city block distance	O(n)	99.6
The proposed method with 128 features	5-levels DWT and 1D-HLP	1NN with city block distance	O(n)	99.6
The proposed method with 256 features	**5-levels DWT and 1D-HLP**	**1NN with city block distance**	O(n)	**99.7**

Table 5
Comparison results for 12, 13, 15 and 17 classes for MIT-BIH arrhythmia database.

Methods	Number of classes	Feature set	Classifier	Computational complexity	Accuracy (%)
Pławiak and Acharya [15]	12 15 17	Frequency components of the power spectral density of the ECG	Deep genetic ensemble of classifiers	$O(n^2)$	98.3 95.4 94.6
Pławiak [52]	15 17	Frequency components of the power spectral density of the ECG	Genetic ensemble of SVM classifiers optimized by sets	$O(n^2)$	93.0 91.4
Pławiak [25]	13 15 17	Frequency components of the power spectral density of the ECG	Evolutionary-Neural System (based on SVM)	$O(n^2)$	94.6 91.3 90.2
Yıldırım et al. [53]	13 15 17	Rescaling raw data	1D-CNN	$O(n^3)$	95.2 92.5 91.3
The proposed method with 64 features	13 15 17	5-levels DWT and 1D-HLP	1NN with city block distance	O(n)	98.5 97.2 94.6
The proposed method with 128 features	13 15 17	5-levels DWT and 1D-HLP	1NN with city block distance	O(n)	99.0 97.4 94.7
The proposed method with 256 features	**13 15 17**	**5-levels DWT and 1D-HLP**	**1NN with city block distance**	**O(n)**	**99.3 97.7 95.0**

of 91%. Recently, convolutional neural network was used to classify the 17 arrhythmia classes [53]. Their study has reported a classification accuracy of 91.3%.

In the present study, we have used a combination of DWT coefficients and 1D-HLP to extract the features. These extracted features are subjected to NCA data reduction technique. The 1NN with city block distance matrix has obtained highest classification compared to the rest of the distance methods. Our proposed method with 256 features coupled with 1NN classifier has yielded a classification accuracy of 99.7%, 99.3%, 97.7%, and 95.0% for 5, 13,15 and 17 ECG classes respectively. The proposed method was compared to state of art methods and comparative results were listed in Tables 4 and 5 for 5, 13, 15 and 17 classes respectively.

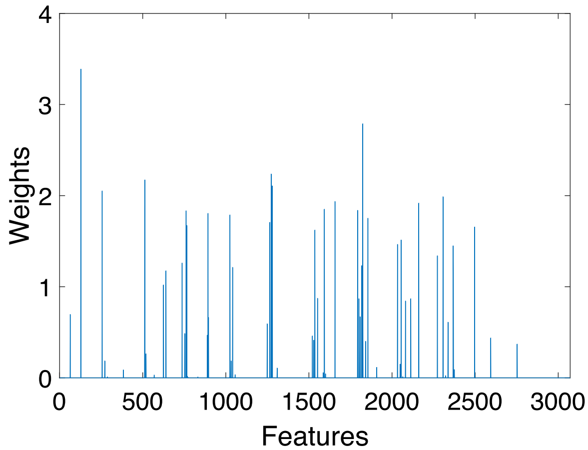


Fig. 8. Schematic diagram of feature values obtained after using NCA.

Table 6
Comparison of our method with other wavelet transform method.

Features	Tunable Q wavelet	Lifting wavelet	1D-DWT
64	93.3%	93.5%	94.6%
128	93.5%	93.6%	94.7%
256	93.7%	93.9%	95.0%

Table 7
Results obtained for various levels of DWT.

Level	Accuracy (%)
0	85.2
1	88.9
2	91.8
3	93.1
4	94.2
5	95.0
6	94.7
7	93.2

The best result is indicated in bold font. The above tables clearly show that our proposed method has yielded better results than the previously reported works.

The reduced 64 features obtained using NCA with 1NN classifier have yielded an accuracy of 94.6%. The 128 reduced features with 1NN have obtained an accuracy of 94.7% and 256 reduced features have got an accuracy of 95.0% using 1NN classifier.

It can be seen in Tables 4 and 5 that, the proposed method has low computational complexity (O(n)). To improve classification capability, optimization methods, deep learning algorithms like CNN, LSTM, U-Net and autoencoders have been used [17,24,65,66]. The prominent aspect of the proposed method is that it has low computational complexity with high classification performance.

1NN is the simplest classifier and fast. Usually it is used when we have more data, and accuracy (%) for various K values are shown in Fig. 10. It can be noted from the below graph that, maximum accuracy can be obtained for $K = 1$ and with increase in K the accuracy falls gradually. Hence, we have chosen $K = 1$ for this work.

As seen from Fig. 10, variable 1NN, 2NN, ..., 10NN are used for testing and these results clearly show that 1NN has the best classification capabilities among all of them.

The performance of the proposed method is compared with other wavelet transform methods namely tunable-Q wavelet (TQWT), lifting wavelet and 1-D DWT method (Table 6).

It can be seen from Table 6 that, the best wavelet transform is the 1D-DWT. Hence, it is used for the ECG signal classification with pooling method in this paper.

The proposed method performed 5 levels of 1D-DWT to obtain the optimum performance. Hence, the minimum size of the signals should be 32. The length of the ECG signals of the used is 3600 samples.

The results obtained for various levels of 1D-DWT is listed in Table 7.

The above results (Table 7) clearly justify the use of 5 levels of DWT decomposition. By using 5 levels DWT, P, QRS and T waves are easily found. Therefore, the best results are achieved using 5 level DWT.

The algorithms developed and published in 2018 [25,52,53] have higher computational complexity as they are based on ensemble learning, deep learning and evolutionary computation methods. Our proposed method has lower computational complexity as it involves only: (a) 5 levels of DWT decomposition, (b) 1D-HLP and (c) NCA based feature reduction method. Therefore, our proposed method is simple and less complex.

Our proposed method has obtained approximately 1.0% improved classification accuracy than the previously presented methods (see Table 5). MIT-BIH Arrhythmia dataset is a heterogeneous dataset. The proposed feature extraction method can be used in other heterogeneous datasets such as electroencephalogram (EEG), electromyogram (EMG) and speech signals to identify the other abnormal classes with high success rates.

Advantages of the proposed method are given below.

- The feature extraction and classification processes has availed approximately 24 ms (see Table 3). Hence, our work used negligible execution time. Hence, it is fast, less complex and lightweight method.
- We have obtained high classification accuracy using our method. Hence, the obtained features are clinically significant.
- A novel multi-layered method is presented. By using 5 levels 1D-DWT and the proposed HLP, variable features are extracted from an ECG signal. A NCA based feature selection method is presented to select distinctive features. The selected features are fed to the simple 1NN classifier. This method does not use any optimization or weight updating method. Therefore, the proposed method is a multilayered cognitive method.

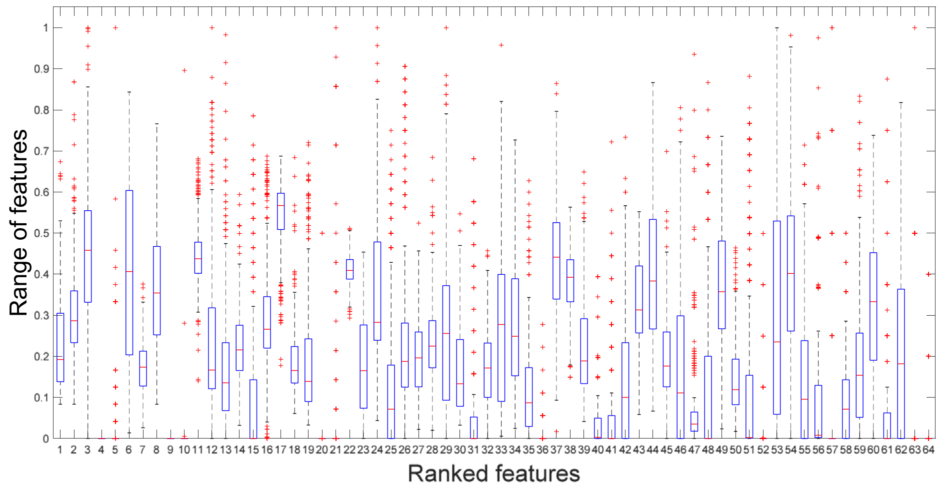
The limitation of the method is that we have used smaller database in each of the 17 classes. Hence, to get more robust results same developed model need to be tested with huge database.

The performance of the developed system can be improved by using other data reductions like: principal component analysis (PCA), locality sensitive discriminant analysis (LSDA), locality preserving projection (LPP) and multiple factor analysis (MFA). The proposed method is a lightweight technique yielding high classification accuracy. Therefore, a cloud based arrhythmia recognition method can be constructed using the proposed method. The graphical illustration of the cloud based system is shown in Fig. 11.

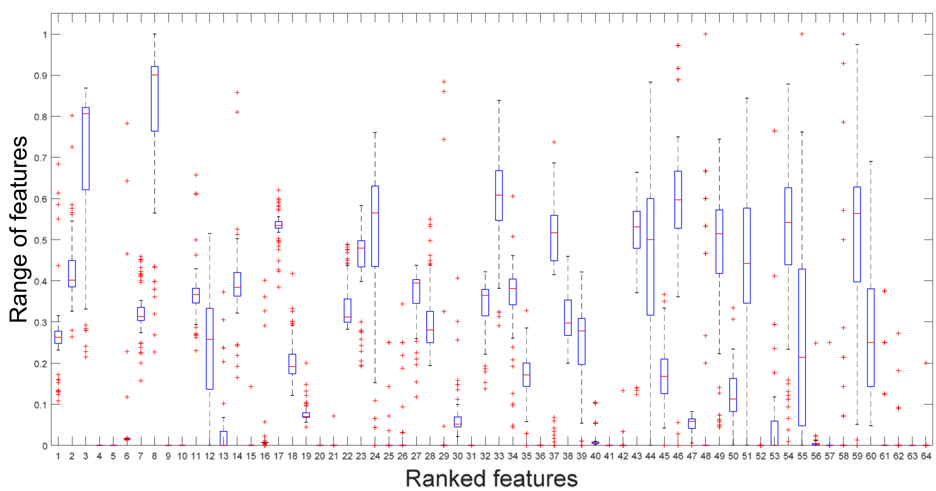
Our developed model can be placed in the cloud. The test ECG signal is sent to the cloud to diagnose the class of the arrhythmia. The class of the ECG will be sent to the mobile phone of the patient immediately and also the diagnosis can be viewed by the clinician to confirm the diagnosis done by our developed model. Hence, it can assist the cardiologists in their diagnosis.

6. Conclusions

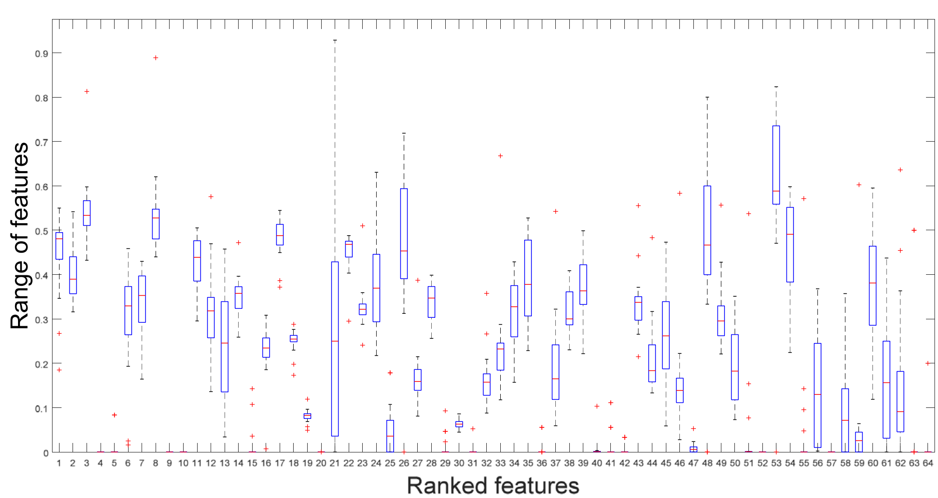
A novel 17 class ECG classification method using DWT and 1D-HLP is proposed in this work. Our proposed system is able



(a) Boxplot of features obtained after NCA for class 1.

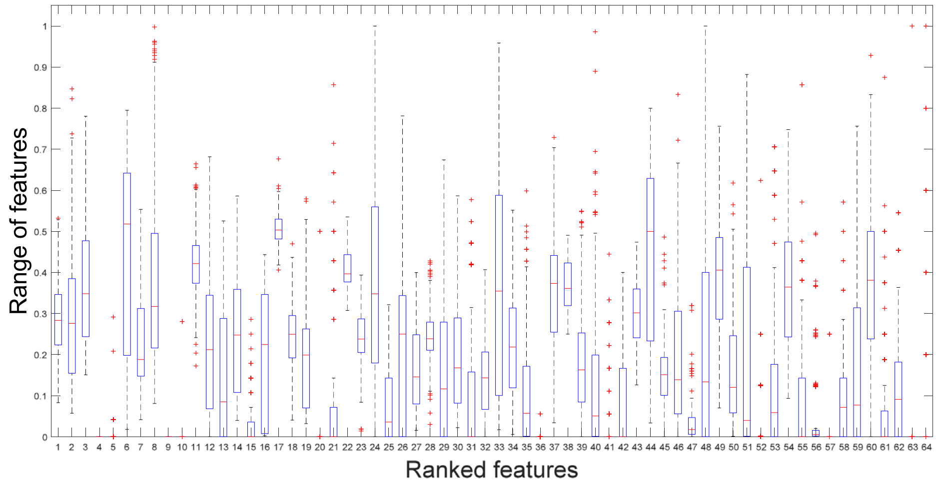


(b) Boxplot of features obtained after NCA for class 2.

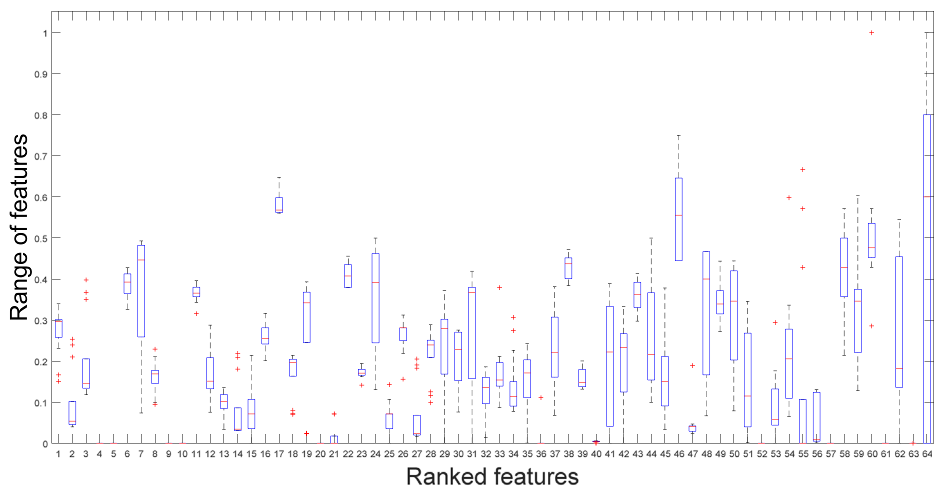


(c) Boxplot of features obtained after NCA for class 3.

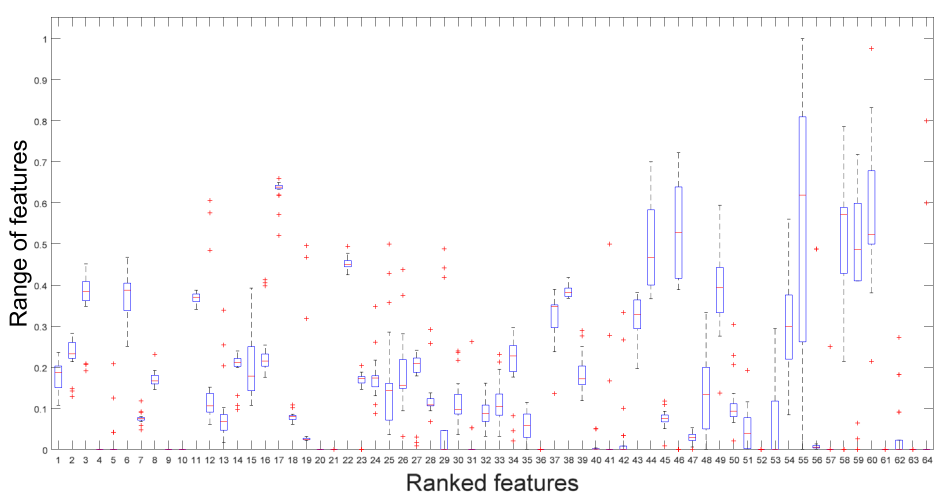
Fig. 9. Boxplots of features obtained after NCA for each class.



(d) Boxplot of features obtained after NCA for class 4.

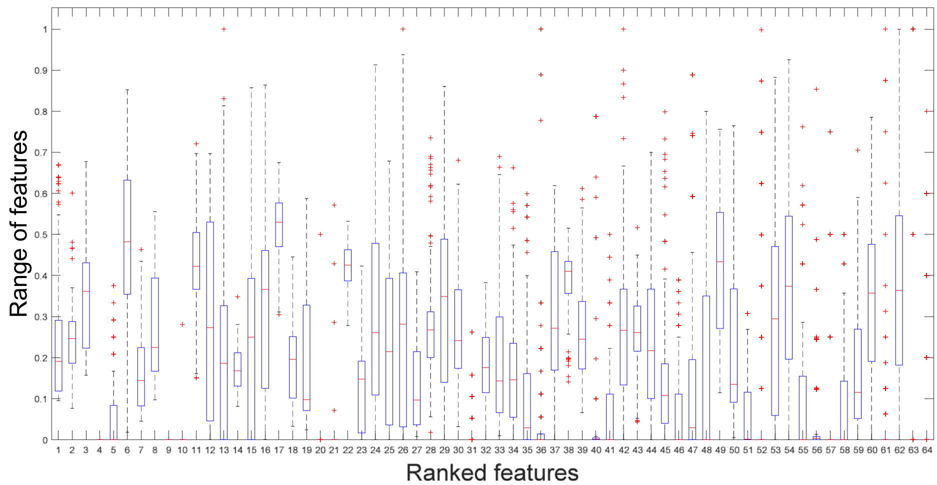


(e) Boxplot of features obtained after NCA for class 5.

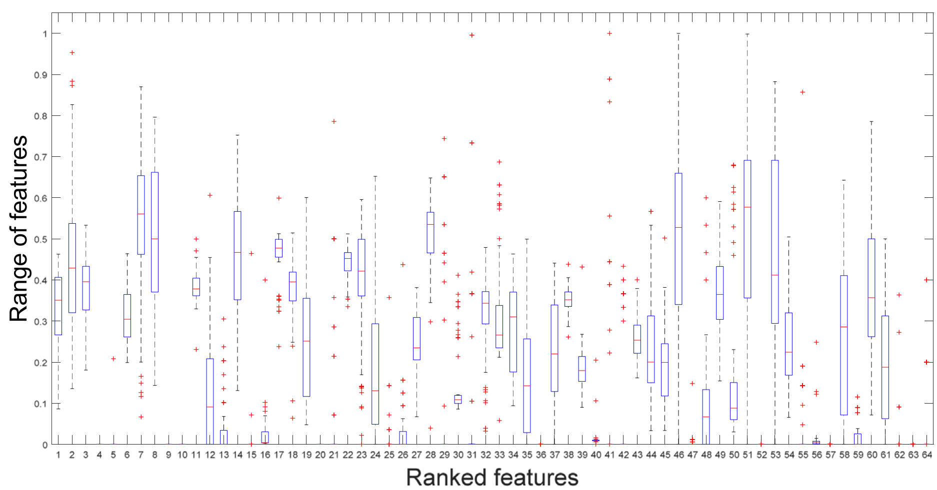


(f) Boxplot of features obtained after NCA for class 6.

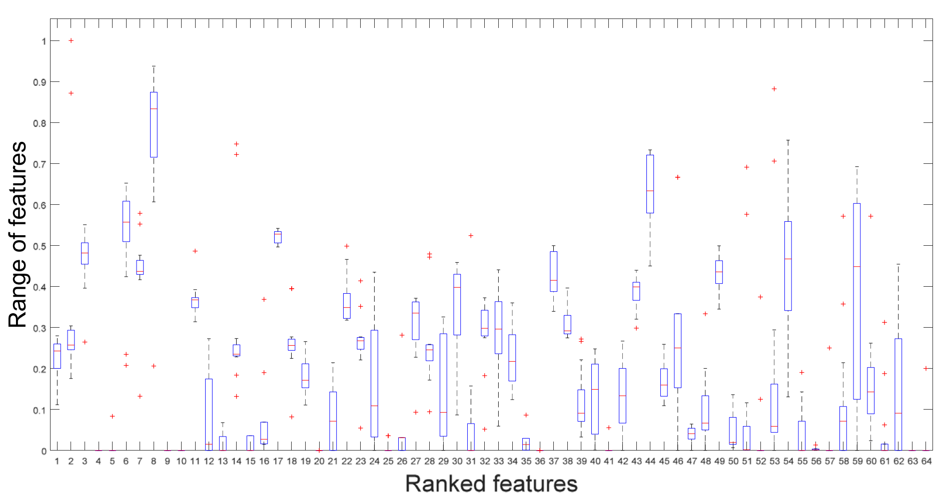
Fig. 9. (*continued*).



(g) Boxplot of features obtained after NCA for class 7.

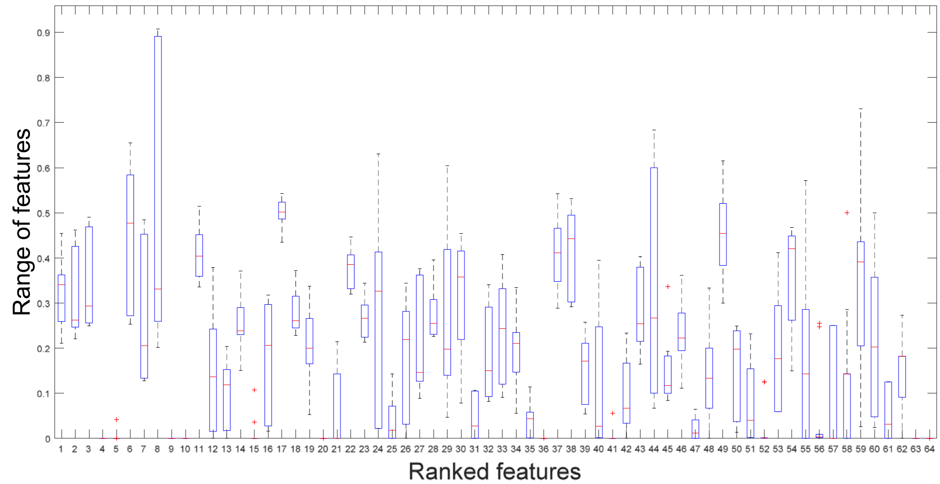


(h) Boxplot of features obtained after NCA for class 8.

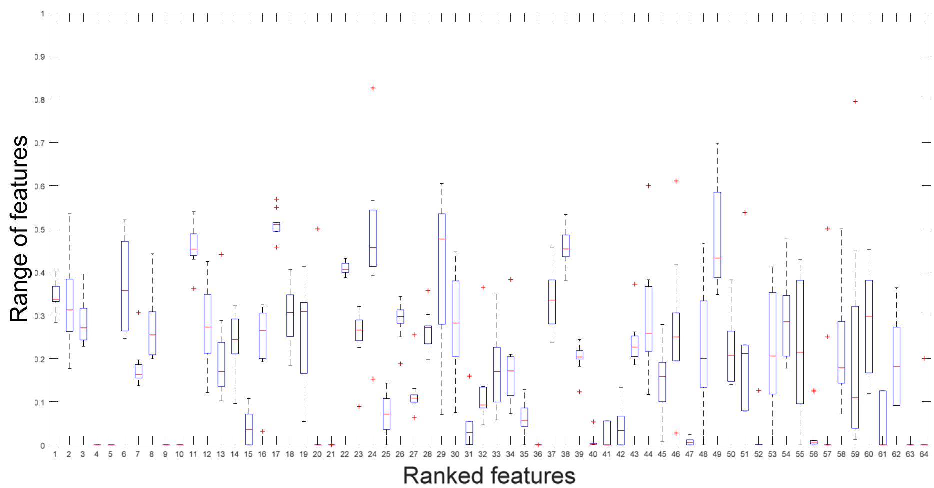


(i) Boxplot of features obtained after NCA for class 9.

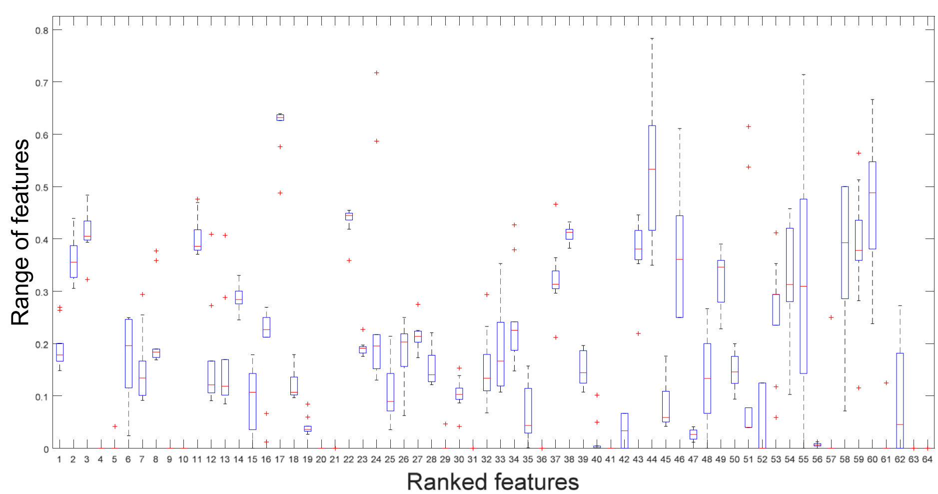
Fig. 9. (*continued*).



(j) Boxplot of features obtained after NCA for class 10.

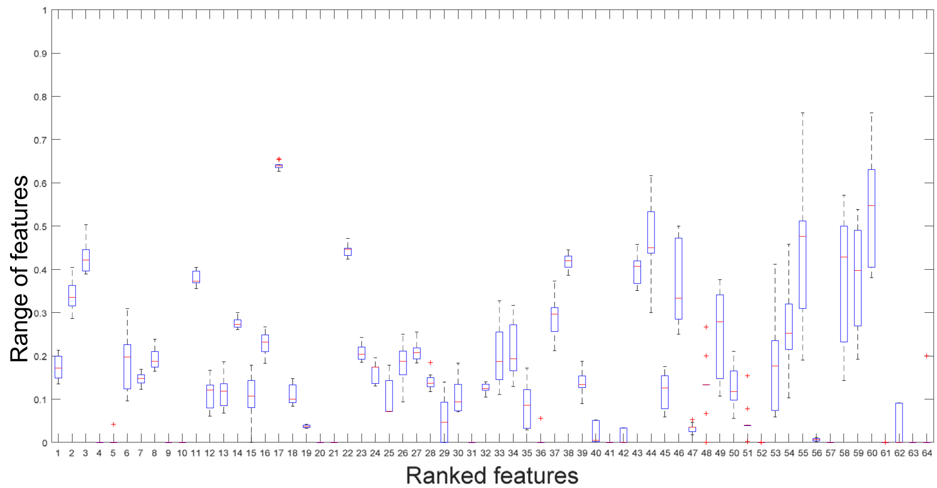


(k) Boxplot of features obtained after NCA for class 11.

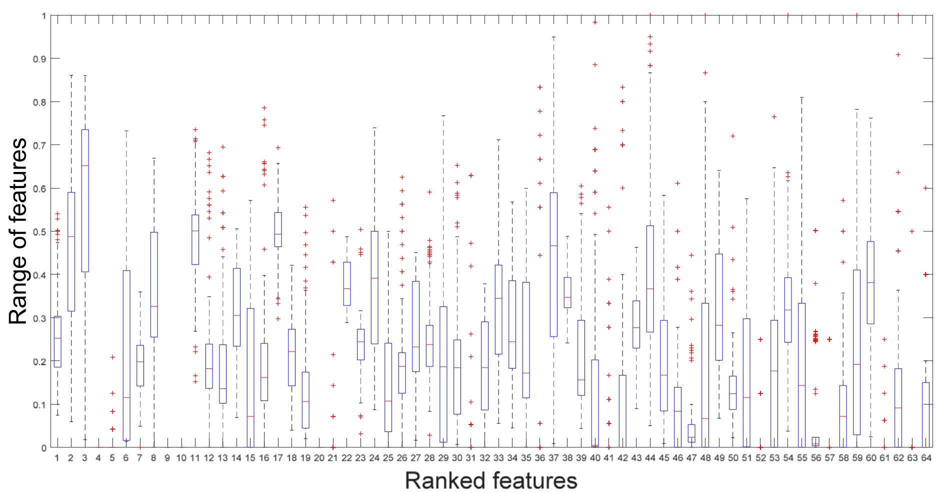


(l) Boxplot of features obtained after NCA for class 12.

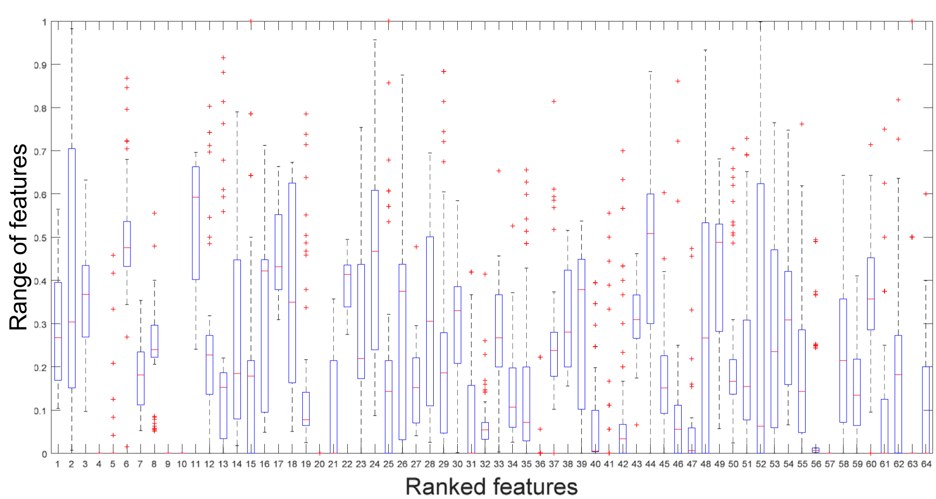
Fig. 9. (*continued*).



(m) Boxplot of features obtained after NCA for class 13.

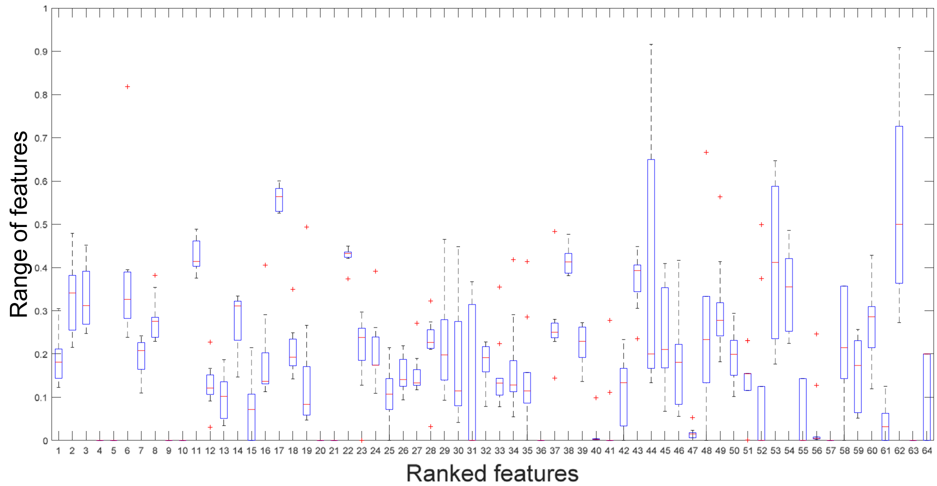


(n) Boxplot of features obtained after NCA for class 14.

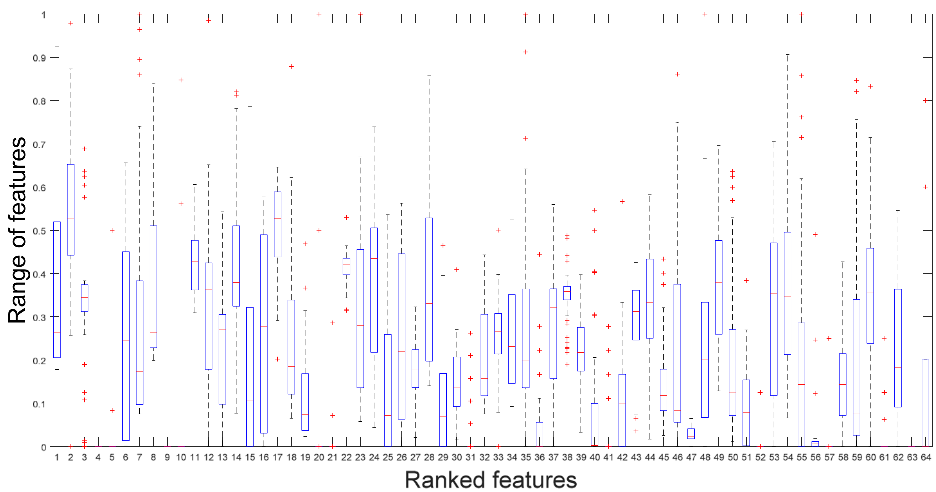


(o) Boxplot of features obtained after NCA for class 15.

Fig. 9. (*continued*).



(p) Boxplot of features obtained after NCA for class 16.



(q) Boxplot of features obtained after NCA for class 17.

Fig. 9. (*continued*).

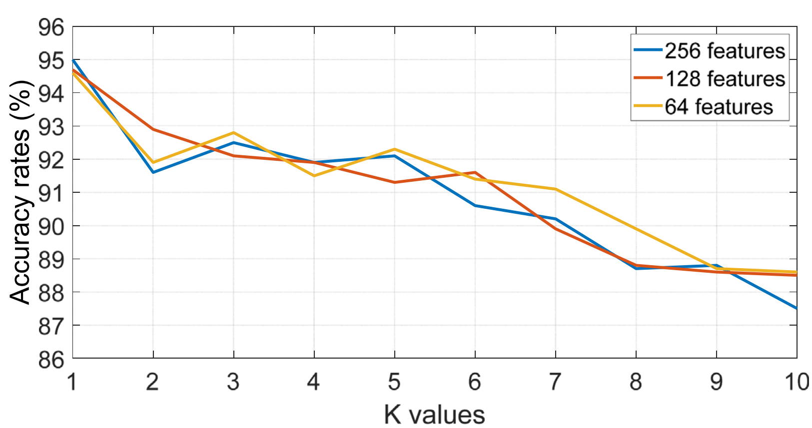


Fig. 10. Graph of accuracy rates (%) for various K values obtained for 64, 128 and 256 features.

to obtained 95.0% accuracy in classifying 17 arrhythmia classes using 1NN classifier with city block distance metrics. The DWT coefficients with 1D local patterns were able to extract the minute changes in the ECG signals which helped to boost the classification accuracy. However, the classification performance can be further improved by using more ECG data in each class and

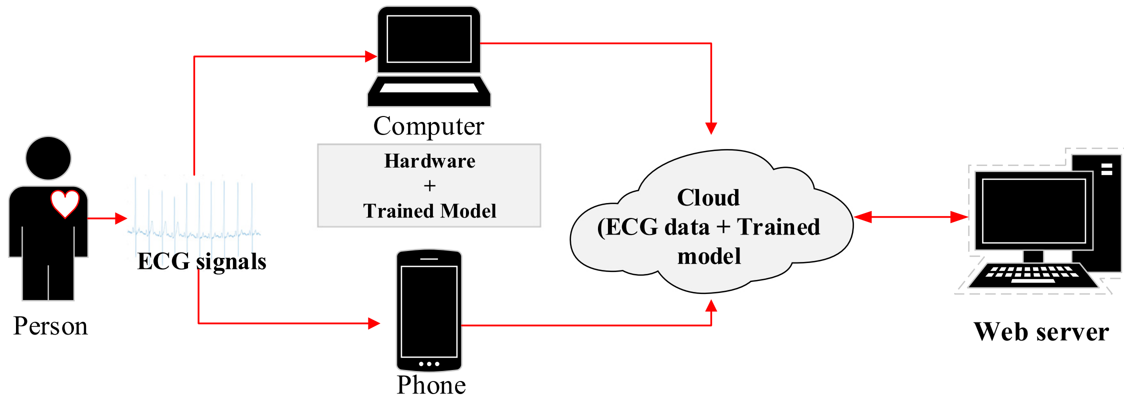


Fig. 11. Illustration of the cloud based model to detect the arrhythmia.

employing deep learning techniques. Also, other 1D local patterns and transformations like empirical mode decomposition (EMD) can be used. Our system can be used to detect other cardiac disease like coronary artery disease, heart failure, and myocardial infarction.

In this work, a novel cognitive and lightweight network is presented for ECG signal classification. Also, novel descriptors (HLP) are used as feature extractors. In future, descriptors based deep feature extraction network can be presented like our proposed method. By using our model, novel intelligent healthcare monitoring systems (Fig. 11) can be developed to get accurate and fast diagnosis.

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