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Research paper

Arrhythmia recognition and classification using kernel ICA and higher order spectra

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Abstract

Electrocardiogram (ECG) is one of the monitoring methodology for the identification of arrhythmia disease. The conventional methodologies of arrhythmia identification are based on morphological features or certain transformation technique. These conventional techniques are partially successful in arrhythmia identification, because it treats heart as a linear structure. In this paper, ECG based arrhythmia identification is assessed by employing MIT-BIH arrhythmia dataset. The proposed approach contains two major steps: feature extraction and classification. Initially, a combination of non-linear and linear feature extraction is carried-out using Principal Component Analysis (PCA), Kernel Independent Component Analysis (KICA) and Higher Order Spectrum (HOS) for achieving optimal feature subsets. The linear experiments on ECG data achieves high performance in noise free data and the non-linear experiments distinguish the ECG data more effectively, extract hidden information and also helps to attain better performance under noisy conditions. After finding the feature information, a binary classifier Support Vector Machine (SVM) is employed for classifying the normality and abnormality of arrhythmia. In experimental analysis, the proposed approach distinguishes the normality and abnormality of arrhythmia ECG signals in terms of specificity, sensitivity and accuracy. Experimental outcome shows that the proposed approach improved accuracy in arrhythmia detection up to 0.5-1% compared to the existing methods: neural network and SVM based radial basis function.

Keywords: *Electrocardiogram; High Order Spectrum; Kernel Independent Component Analysis; Principal Component Analysis; Support Vector Machine.*

1. Introduction

ECG signifies the summation of the inhibitory potential of heart and it is also utilized for diagnosing several cardiac disorders like arrhythmia [1], [2]. Arrhythmia is the second most common syndrome of the heart and also one of the common cardiac disorder that affects a significant percentage of the world population [3]. Approximately, 15% of the world population suffer from arrhythmia [4]. There are numerous causes for arrhythmia, most of them are associated with cardiovascular disease. Arrhythmias like flutter and ventricular fibrillation are life-threatening medical emergencies, which result in sudden death, cardiac arrest and hemodynamic collapse. Presently, arrhythmia identification is accomplished by medical physician based on visual observation of ECG signals [5], [6]. So, an automatic arrhythmia identification has multifarious benefits over human visual inspection such as, faster diagnosis, less time consuming for identifying arrhythmia from ECG records, easily handle large datasets, etc. [7].
In current scenario, the automatic arrhythmia identification is a challenging task in the medical field [8]. Several research articles have been implemented for enhancing the classification accuracy of ECG system, but still these methods can't achieve satisfactory results in arrhythmia prediction [9], [10]. In this research, to improve the classification accuracy, an effective scheme is implemented for investigating the ECG data. A variety of methods like, mean, covariance, correlation, entropy features, etc. are extensively employed to extract the features from ECG signals. Among these features, a combination of linear and non-linear features (PCA, KICA and HOS) are employed to describe and distinguish the ECG data. The advantage of both linear and non-linear features helps to achieve optimal feature subsets. The outcome of non-linear and linear features are classified using SVM classification method and the proposed outcome is compared with the existing classifiers like Neural Network (NN), SVM-Radial Basis Function (SVM-RBF). The goal of using SVM classifier for arrhythmia classification, if there is no prior knowledge about the distribution of the data, the SVM method should be one of the first choices for classification. Finally, the classification outcome confirms that the proposed technique provides an effective result in arrhythmia identification and classification.
This paper is composed as follows. Section II presents a broad survey of several recent papers on arrhythmia identification and classification. In section III, classification methodology (SVM) is presented with an effective linear and non-linear features. In Section IV, comparative study of proposed and existing methodology is presented. The conclusion is made in Section V.

2. Literature review

Several techniques have suggested by researchers in the arrhythmia identification and classification. In this scenario, brief evaluations of some important contributions to the existing literatures are presented.
M. Thomas, et al. [11] presented a new technique for automatic arrhythmia prediction using Dual Tree Wavelet Transform (DTCWT). In addition, the proposed technique comprises of four

features (kurtosis, skewness, AC power and timing information) for extracting the optimal feature vectors. These feature sets were classified using multi-layer back propagation neural network. The proposed technique achieves better performance by means of specificity, sensitivity and accuracy compared to existing methodology: Discrete Wavelet Transform (DWT). Whereas, the DTCWT method consumed more time for implementing the hardware related parameters.

J.S. Wang, et al. [12] proposed a new technique that was the combination of both feature extraction (PCA and Linear Discriminant Analysis (LDA)) and classification approach (Probabilistic Neural Network (PNN)) for classifying eight dissimilar types of arrhythmia from ECG signal. Simulation outcome confirmed that the proposed technique performed effectively by means of classification accuracy. In a few cases, the training signals were dependent evaluation or manual adjustment, which was needed to be automated.

P. Melin, et al. [13] proposed a new machine learning network using Learning Vector Quantization (LVQ) system for classifying the ECG signals. In this literature, the MIT–BIH arrhythmia dataset with 15 classes and three architectures were utilized for experimental analysis. Compared with other existing methods, the proposed technique delivered a very good result. Simulation results were presented, and a statistical investigation was carried out for comparing the three architectures, which were similar in the classification results. If the number of samples were low, the LVQ algorithm was highly affected in the training set that decreases the performance by means of classification accuracy.

M. Moavenian, and H. Khorrami, [14] proposed a new learning system named as Kernel Adatron (KA) learning system to aid SVM for ECG arrhythmias classification. The proposed pattern classifier was compared with Multi-Layered Perceptron (MLP) using back propagation learning system. Extensive experiments were conducted and the efficiency of the proposed approach was verified using MIT-BIH arrhythmia dataset. In a large dataset, the proposed technique failed to achieve better arrhythmia classification performance by means of accuracy.

Y. Özbay, and G. Tezel, [15] proposed a new technique named as Neural Network based Adaptive Activation Function (NNAAF) for classifying the ECG arrhythmias. The proposed methodology consists of three types of activation functions: NNAAF 1, NNAAF 2 and NNAAF 3 with adaptable free parameters were utilized in hidden neurons for enhancing the classical MLP network. The experimental research was performed on a reputed dataset (i.e. MIT-BIH arrhythmia dataset) to validate its classification accuracy. Computational time was a bit high in the proposed methodology compared to other existing approaches, while clustering the signal in large dataset.

S.K. Dash, and G.S. Rao, [16] presented a new methodology for ECG signal classification. Initially, the ECG signals were acquired from the database: MIT-BIH arrhythmia dataset. Then, a three-layer feed forward backpropagation neural network was utilized as a classification methodology. The training data were taken from the label and test the data with the signal for classifying the ECG signal. The proposed methodology achieves high accuracy, sensitivity and specificity up to 99.24%, 94.90% and 99.57% respectively. One of the major drawback of proposed methodology was high computational time compare to the other conventional methods.

R.R. Linhares, [17] proposed a new methodology, which was the combination of smoothed detrended fluctuation analysis (SDFA) and principal of wavelet shrinkage scaling analysis technique for representing the time series correlation properties. The extensive experiments were conducted and the efficiency of the proposed methodology was verified by means of mean square error. The proposed ECG system (SDFA) fails to attain better classification performance in terms of accuracy, when the acquired dataset was high.

To overcome the above mentioned issues, an effective combination of non-linear and linear features are implemented with an appropriate binary classifier: SVM for enhancing the performance of arrhythmia identification and classification.

3. Proposed methodology

The proposed automated arrhythmia prediction system contains the following procedures: segmentation, feature extraction and classification. Figure.1 shows the general block diagram of the proposed system. Each part of the proposed work is explained briefly in the following sections.

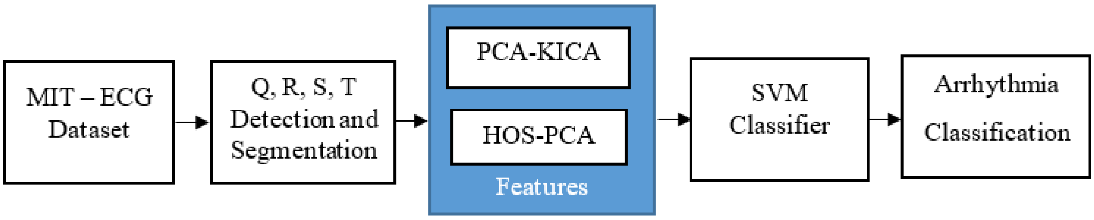

Fig. 1: General Block Diagram of Proposed Methodology.

3.1. Material and methods

In the initial stage of the arrhythmia prediction system, the input ECG signals are taken from the standard benchmark dataset: MIT BIH arrhythmia dataset. The respective dataset contains 48 half hour excerpts of two channel ambulatory ECG data acquired from 47 subjects examined by the BIH arrhythmia Laboratory between 1975 and 1979. Twenty-three records were haphazardly taken from a set of 4,024 hours ambulatory ECG data gathered from an individual including the two inpatients (around 60%) and outpatients (around 40%) at Boston's Beth Israel Hospital [18].

Remaining 25 records were chosen from a similar set in order to incorporate clinically significant arrhythmias. The ECG records are examined at 360 Hz. Per channel includes11 bit resolution more than 10 mV extend. In this paper, absolutely 24,989 anomalous and 10,000 normal signals are utilized. In that, 7126 beats are Ventricular Premature Contraction (VPC), 7250 beats are Right Bundle Branch Block (RBBB), 2544 beats are Atrial Premature Contraction (APC) and 8069 beats are Left Bundle Branch Block (LBBB). A brief description about the various kinds of ECG beats are explained below.

- Normal beat: The normal ECG beat comprises of peaks: P, QRS complex and T wave. The PR peaks range between 120 ms and 200 ms and the heart rate interval ranges between 60 and 100 beats per minute.
- RBBB: The QRS complex of the ECG signal demonstrates an additional diversion, which indicates the quick depolarisation of the left ventricle followed by the slower depolarisation of the right ventricle.
- LBBB: The activation of the left ventricle is delayed, which results in the compression of left ventricle later than the right ventricle. The length of the QRS complex exceeds 120 ms.
- APC: It is described by early heartbeats starting in the atria. The sinoatrial node directs the pulse amid normal sinus rhythm, APCs happen when another region of the atria de-

polarizes earlier than the sinoatrial node and it triggers a premature beat.

- VPC: Issue exists outside the SA node, the QRS complex is extended, not related with the following P wave and T wave is inverted. The acquired dataset is utilized for non-linear and linear feature extraction.

3.2. Kernel independent component analysis

Generally, ICA is a texture descriptor that helps to separate the multi-variate features into additive sub-components. Whereas, the additive sub-components are non-Gaussian approach that is statistically free from the other independent scheme. In this scenario, the ICA helps to solve the higher order data and also determines the independent source point for components from their linear structure. Hence, ICA delivers a significant data representation by applying image decomposition and representation. Usually, estimated independent components are achieved by applying an effective algorithm, which is very tough to define the energies and the order of independent components. A vector of unknown source is represented as S with a linear combination of several vectors are given in the equation (1).

$$X(t) = AS(t) \tag{1}$$

Where, $X(t)$ is composed with m signal observation matrices, $S(t)$ is stated as independent component, A is denoted as mixed matrix $M \times N$ and t is denoted as time. Using observational signal $X(t)$, a transformation W is occurred that obtains source signal value $\mathrm{Y}(t)$, which is mathematically represented in the equation (2).

$$\mathrm{Y}(t) = WX(t) = WAX(\mathrm{t}) \tag{2}$$

The features extracted from ICA are linear, so the outcome of the classification is highly complex or non-linear structure. To overcome this issue, several ICA algorithms proposed that differ in their objective functions of statistical independence. For fast computation and efficient dimensional reduction, Kernel-ICA method is employed. Kernel-ICA is an adequate and well-known algorithm for ICA, which is based on a fixed-point reiteration approach. This algorithm maximizes the non-Gaussian statistical independent measure. The commonly utilized kernel functions are signified in the equations (3), (4) and (5).
Linear Kernel:

$$K(x_i, x) = (x.x_i) \tag{3}$$

Polynomial Kernel:

$$K(x_i, x) = ((x.x_i) + \mathrm{c})^d \; c \geq 0 \tag{4}$$

Radial basis function (RBF) Kernel:

$$K(x_i, x) = \exp\left(\frac{\|x_i - x\|^2}{2\sigma^2}\right)\sigma \geq 0; \tag{5}$$

Among these kernel functions, RBF kernel is selected in this paper. The steps involved in RBF kernel is briefly represented below.
Step1: Input is ECG data and identify the number of source m.
Step2: Initialize the separation matrix W
Step3: Calculate the source signals $S_i = Wx_i$ and then determine the centralized gram matrix $K_1, \ldots, K_m$.
Step4: Determine the minimum eigenvalue $\lambda_F(K_1, \ldots, K_m)$ of the generalized characteristic vector equation $K\alpha = \lambda D\alpha$.
Step5: Determine the objective function using the equation (6).

$$C(W) = -\frac{1}{2}\log_2 \lambda_F(\mathrm{K}_1, \ldots\ldots\ldots, \mathrm{K}_m) \tag{6}$$

Step6: Decrease the objective function and output S.
For instance, ECG signal x_i is composed with a set of independent base signals. The independent signals are obtained from kernel-ICA decomposition using n cycles of ECG signal matrix $X = (X_1, X_2, \ldots\ldots X_n)^T$. The co-efficient of each ECG signal is projected from direction B by extracting the non-linear feature vector from independent base signals. The pseudo-inverse technique is utilized in the equation (7) for identifying the projection coefficient vector.

$$A_i = x_i \times S^+ \tag{7}$$

Where, S^+ is represented as the pseudo-inverse matrix of the independent component S, and A_i is stated as the feature vector of the identified ECG signal. The proposed Kernel-ICA decreases the power frequency interference and also provides fast computation and efficient dimensional reduction.

3.3. High order spectrum

The HOS is denoted as cumulants or Higher Order Moments (HOM). Generally, HOS is the multi-dimensional Fourier transforms, which helps to achieve higher order statistics. Here, the HOM invalidates all Gaussian random effects procedure, and the bicoherence quantifies the degree of remaining nonlinear coupling. In HOS, the third order statistics are named as bispectrum. The bispectrum $B(f_1, f_2)$ and normalized derivative of the ECG signal describes the third order correlation of Fourier transform, which is given by averaged biperiodogram. Mathematically, it is represented in the equation (8).

$$B(f_1, f_2) = \mathrm{E}[\mathrm{X}(\mathrm{f}_1)\mathrm{X}(\mathrm{f}_2)\mathrm{X}^*(\mathrm{f}_1 + \mathrm{f}_2)] \tag{8}$$

Where, $X(f)$ is denoted as the Fourier transform of ECG signal $x(nT)$, $*$ is stated as the conjugation operator, $E[.]$ is represented as the average ensemble of random ECG signals. In deterministic sample signals, $X(f)$ is denoted as the discrete time Fourier transform, which is computed with discrete samples using fast Fourier transform algorithm. The frequency f is normalized between 0 to 1.
The bispectrum equation (8) is a complex function and the Fourier transform for real ECG signals are conjugate symmetric. The bispectrum is computed in non-redundant regions or in a principal domains. Assume, if there is no bispectral aliasing, then the bispectrum of real valued ECG data is defined in triangle $0 \leq f_2 \leq f_1 \leq f_1 + f_2 \leq 1$. The non-redundant region is represented as Ω, which is also stated as principal domain. The principal domain Ω inside the triangular region is represented in the figure 2.

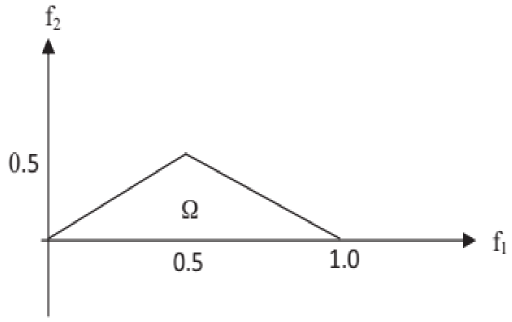

Fig. 2: Bispectrum Computation of Principal Domain Is Exposed Inside the Triangle.

3.4. Principal component analysis

PCA is the statistical methodology utilized to reduce the dimension of data (signal) and also used for extracting the useful features of ECG signals. Various techniques are preferred in arrhythmia identification and classification, but the performance of PCA is very effective, because it factorize the target signal and sparse the noise effectively. Also, PCA gives more attention on covariance and variance structure of the new variables $x_1, x_2, x_3, ...x_p$. These variable magnitudes are much higher than the other variables, because these new variables receive heavy weights.
To avoid this reason, the variables are determined on scales with different ranges, otherwise the unit of the measurements are not equal. Let, R be the sample correlation matrix calculated from n observations on each principal component p of random variables. The Eigen-value and Eigen-vector pairs of R is represented as $(\varepsilon_1, e_1), (\varepsilon_2, e_2), (\varepsilon_3, e_3), ...(\varepsilon_p, e_p)$. The $i-th$ ample principal component of a vector $x = x_1, x_2, x_3, ...x_p$ variable is given in the equation (9).

$$e_i^z = e_{i1}Z_1 + e_{i2}Z_2 + ...e_{ip}Z_p,\ i = 1,2,3,..\mathrm{p} \tag{9}$$

Where, $e_iZ = (e_{i1}, e_{i2}, ...e_{ip})$ represents $i-th$ Eigen value and $z = z_1, z_2, z_3, ...z_p$ is stated as the standardized vector observation.
In principal component, the sample variance is represented as n_i and the sample covariance pairs are mentioned as zero. In addition, the total sample variance in all standardized variables is equal to the total sample variance in the principal component. Mathematically the standardized vector observation is expressed in the equation (10).

$$Z_k = \frac{x_k - \bar{x}_k}{\sqrt{v_{kk}}}, k = 1,2,3...p \tag{10}$$

Where, x_k denotes sample mean and v_{kk} is the sample variance of the variable x_k. The samples of different ECG signal is represented in the figure 3.

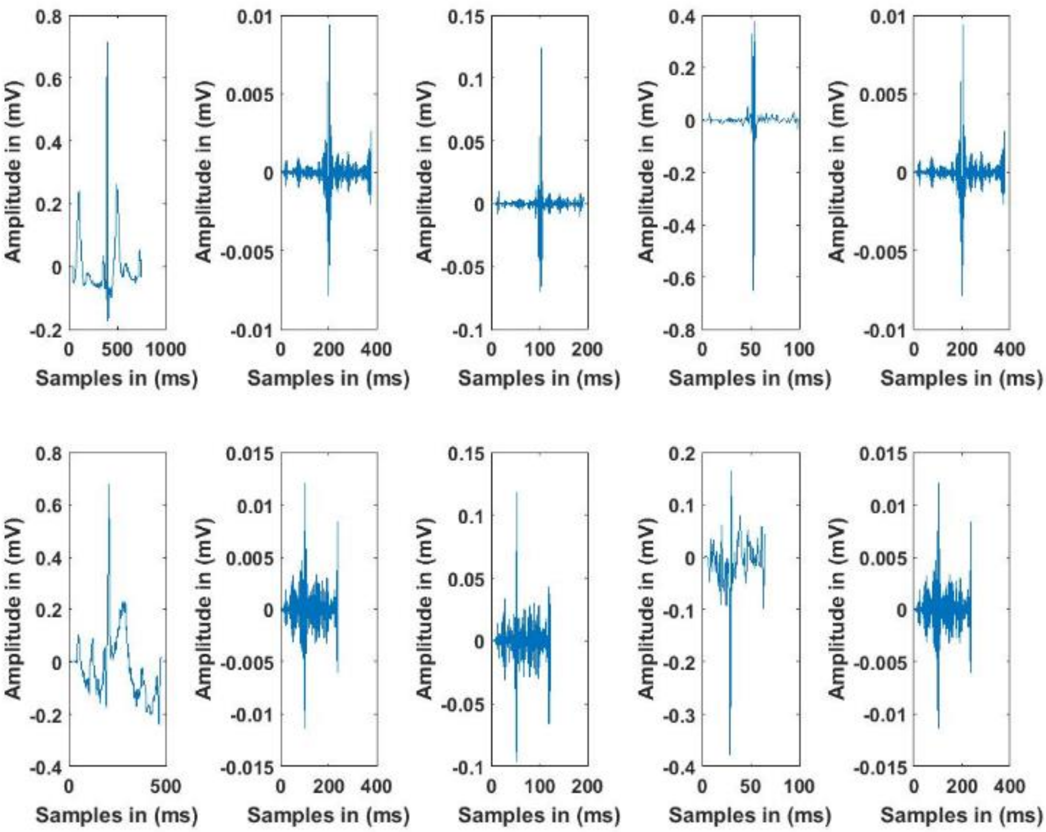

Fig. 3: Samples of Different ECG Signal.

3.5. Support vector machine

After performing feature extraction, classification is carried out using SVM, which enables an efficient way of extracting the features and a set of rules to perform classification. SVM is a discriminative classification approach represented by a separate hyperplane. The goal of SVM is to train the classifier utilizing training data and generate an optimal model, also if there is no prior knowledge about the distribution of the data, SVM method should be one of the first choices for classification. The SVM classifier is popularly used in several applications like bioinformatics, signal processing, computer vision fields, etc., due to its high performance in accuracy, ability of processing the high dimensional data problems such as, gene expression and modelling of diverse data source.

SVM is a kind of classifier, it does well in solving two-class problem, which is associated with the theories of Vapnik–Chervonenkis (VC) and structure principles. Significant generalized ability is determined by comprising the model complexity. The General formula for the linear discriminant function is symbolized as $w.x + b = 0$. An optimum hyperplane is required to distinct the samples without noise and also to exploit the gap between two groups. It is satisfied by implementing the equation (11),

$$pi[w.x + b] - 1 \ge 0,\ \mathrm{i} = 1,2,..,\mathrm{N} \tag{11}$$

In the above formula, diminish $\|w\|^2$, so this optimization issue is solved by the saddle point of a Lagrange function with Lagrange multipliers. Ideal discriminant function is mathematically specified in equation (12),

$$f(x) = \operatorname{sgn}\{(w^* x) + b^*\} = \operatorname{sgn}\{\sum_{i=1}^{N} \alpha_i^* . pi\,(x_i^* . x) + b^*\} \quad (12)$$

Then, replace the interior product by a kernel function $k(x, x')$ in formula (13), to solve large computational complexity in the high dimensions. In this way, the linear separability of estimated samples are improved and the discriminant function is re-written as follows,

$$f(x) = \operatorname{sgn}\{\sum_{i=1}^{N} \alpha_i^* . pi . k(x_i^* . x) + b^*\} \quad (13)$$

Totally, three dissimilar types of kernel functions are commonly used, they are linear, polynomial and sigmoid kernels in nature.

4. Experimental outcome

In this scenario, for experimental simulation, MATLAB (version 2017a) was employed on PC with 3.2 GHz with i5 processor. To determine the efficiency of the proposed algorithm, the proposed technique performance was compared with NN, SVM-RBF classifier on the reputed database: MIT-BIH arrhythmia dataset. The proposed technique performance was compared by means of sensitivity, accuracy and specificity.

4.1. Performance evaluation

The relationship between the input and output variables of a system understand by employing the suitable performance metrics like sensitivity and specificity. The general formula of sensitivity and specificity for classifying the normality and abnormality of arrhythmia disease is given in the equation (14) and (15).

$$Sensitivity = \frac{TP}{TP + FN} \times 100 \quad (14)$$

$$Specificity = \frac{TN}{TN + FP} \times 100 \quad (15)$$

Where, TP is denoted as true positive, FP is denoted as false positive, TN is stated as true negative and FN is stated as false negative.

In addition, accuracy is the suitable evaluation metric for finding the efficiency of normal and abnormal activities of the heart. The general formula of accuracy for classifying the normality and abnormality of arrhythmia disease is given in the equation (16).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \quad (16)$$

4.2. Result for MIT-BIH arrhythmia dataset

In this experimental analysis, for comparing the performance evaluation of existing methods and the proposed scheme, 80% of training and 20% of testing is assessed on MIT-BIH arrhythmia dataset. In table 1, the sensitivity of the proposed technique is 99% and the existing approaches delivers 98.91% and 98.90% of sensitivity. Similarly, the specificity of the proposed technique is 99.08%, and the existing approaches delivers 97.85% and 98.90% of specificity. The graphical comparison of sensitivity and specificity for MIT-BIH arrhythmia dataset is denoted in the figure 4.

Table 1: Performance Comparison (Sensitivity and Specificity) of Proposed and Existing Methodologies

Classifiers	Features	Sensitivity (%)	Specificity (%)
SVM-RBF [19]	PCA-DWT + ICA-HOS	98.91%	97.85%
NN [19]	PCA-DWT + ICA-HOS	98.90%	98.90%
SVM [proposed]	KICA-PCA PCA-HOS	99%	99.08%

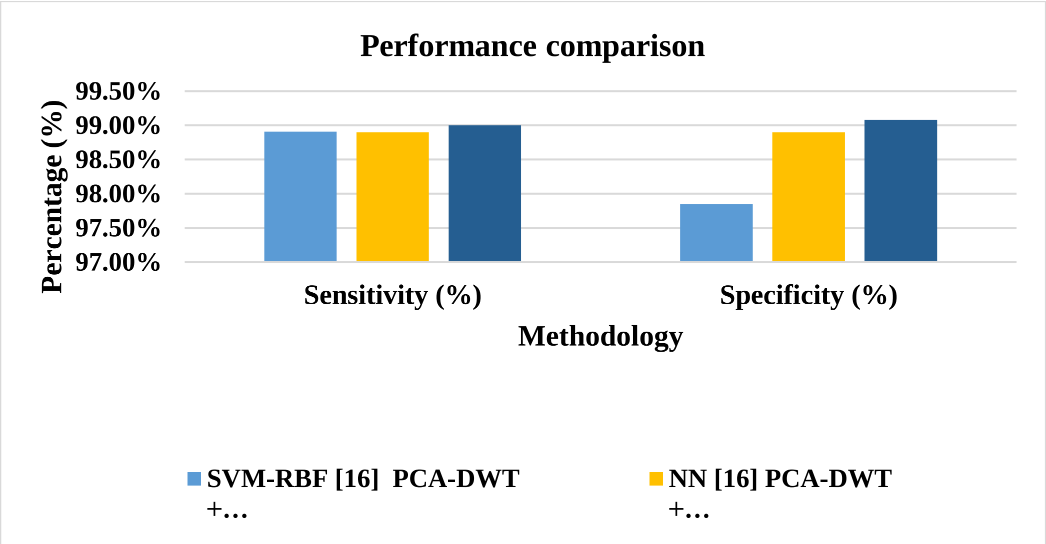

Fig. 4: Graphical Comparison of Sensitivity and Specificity for Proposed and Existing Methodologies.

Table 2 compares the arrhythmia classification accuracy of existing approaches and the proposed approach. The existing methodologies like PCA-DWT, ICA-HOS, PCA-DWT+ICA-HOS and PCA-KICA using SVM-RBF and NN classification methods achieves 88.04%, 93.48%, 97.83%, 94.57%, 98.91%, 98.90%, 97.14% and 98.5% of classification accuracy. Instead, the proposed approach achieves 99.04% of classification accuracy using KICA-PCA-PCA-HOS and SVM methodologies. The table 1 and 2 confirmed that the proposed approach performs effectively compared to the existing methods on the MIT-BIH arrhythmia dataset. The graphical comparison of accuracy is denoted in the figures 5 and 6.

Table 1 and 2 shows the performance evaluation of existing methodologies and the proposed method. Here, the proposed approach able to capture the non-linear characteristics of the ECG signals and preserve quantitative relationships between the low level and high level feature variables. The evaluation metrics confirms that the proposed scheme performs significantly in arrhythmia classification compared to previous methods in terms of accuracy, sensitivity and specificity.

Table 2: Performance Comparison (Accuracy) of Proposed and Existing Methodologies

Classifiers	Features	Classification accuracy
SVM-RBF [19]	PCA-DWT	88.04%
NN [19]		93.48%
SVM-RBF [19]	ICA-HOS	97.83%
NN [19]		94.57%
SVM-RBF [19]	PCA-DWT + ICA-HOS	98.91%
NN [19]		98.90%
SVM [20]	PCA-KICA	97.14%
NN		98.5%
NN	KICA-PCA PCA-HOS	99%
SVM [proposed]		99.04%

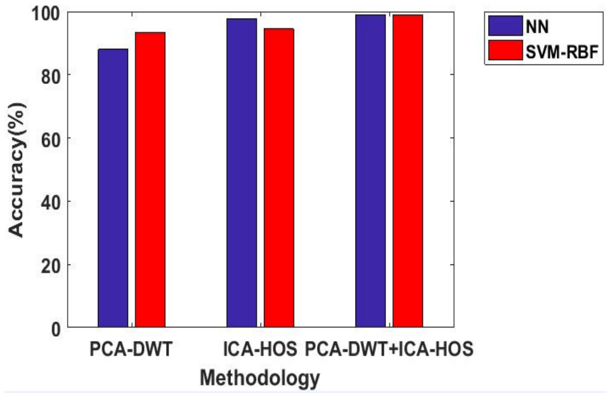

Fig. 5: Accuracy Comparison of Existing and Proposed Methodology.

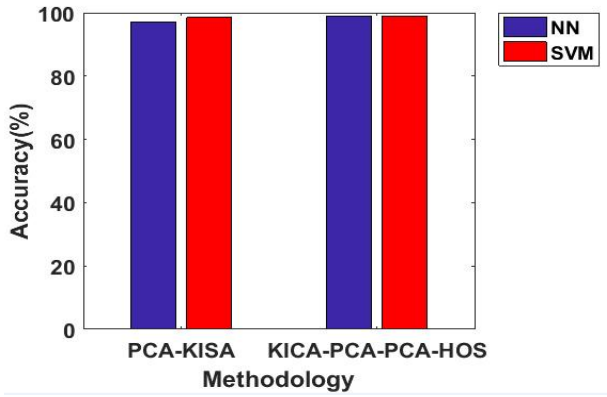

Fig. 6: Accuracy Comparison of Existing and Proposed Methodology.

4.3. Comparative analysis

The table.3 presents the comparative study of existing work and the proposed work performance. F.A. Elhaj, et al. [19] proposed a new arrhythmia prediction methodology using a combination of non-linear and linear features (PCA, DWT, ICA, HOS). After obtaining the feature information, a binary classifier (SVM-RBF) was employed for classifying the ECG signals. This experiment was carried out on a publicly available database (i.e., MIT-BIH arrhythmia dataset) to validate its result by means of accuracy and achieved 98.91%of accuracy. In addition, A.E. Zadeh, et al. [20] presented a new methodology, which was the combination of PCA-KICA (feature extraction) and SVM (classifier). This experiment was also performed on MIT-BIH arrhythmia dataset and achieved 97.14% of classification accuracy. Whereas, the proposed work achieves 99.04% of accuracy that was higher than the existing work.

Table 3: Comparative Analysis of Existing and Proposed Work

References	Database	Features considered	Classification method	Accuracy
F.A. Elhaj, et al. [19]	MIT-BIH arrhythmia dataset	PCA-DWT ICA-HOS	SVM-RBF	98.91%
A.E. Zadeh, et al. [20]	MIT-BIH arrhythmia dataset	PCA-KICA	SVM	97.14%
Proposed work	MIT-BIH arrhythmia dataset	KICA-PCA PCA-HOS	SVM	99.04%

5. Conclusion

ECG signal based arrhythmia disease prediction is one of the most significant research tasks in computer-aided health monitoring system. The objective of this experiment was to develop a proper feature for classifying the normality and abnormality of arrhythmia disease using MIT–BIH arrhythmia dataset. In this scenario, non-linear and linear features (PCA, KICA and HOS) are employed for attaining optimal feature subsets and irrelevant feature rejection. Using these feature information, the normality and abnormality of arrhythmia disease is classified using SVM classifier. Associated to other obtainable approaches in arrhythmia detection, the proposed scheme delivered an effective performance by means of accuracy, sensitivity and specificity, around 0.5-1%, enhancement than the previous methods. In the future work, for further improving the classification rate of arrhythmia diseases, appropriate feature extraction methodologies are combined with binary learning classification methodology.

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