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Cardiac Arrhythmia Detection on Electrocardiogram Beats based on KPCA and SVR

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ABSTRACT: Patients suffer from various heart diseases may lead to sudden death. So that prior detection of arrhythmia is important to prevent the sudden deaths. Developing the methods of ECG signal features extraction is required to detect heart abnormalities and different kinds of diseases. This study shows the arrhythmia detection system based on kernel-PCA and support vector regression. Feature of ECG signal are the interval between the points such as RR interval, P, R, Q, S, and T beats having the specific magnitude. The several methods have been proposed to recognize and analyze the ECG signals. In this paper, we employ the combination of kernel-PCA and support vector regression classifier to recognize the ECG signal. The method consists of three steps; first, low pass filter removes the noise in ECG signal. Then Kernel-PCA and higher order statistics are derived for feature extraction of ECG signal. Finally, the obtained feature set is used as input to SVR classifier to classify the ECG signal. Most of the data comes from online MIT-BIH dataset to obtain the ECG records for evaluating the classification performance. The classification performance of the proposed model is also compared with the several conventional machine learning classifiers, which is better classification accuracy.

Keywords: ECG signal, feature extraction, Principal Component Analysis, Arrhythmia detection, Super vector machine and SVR (Super Vector Regression)

Abbreviations : CNN, Convolution Neural Network; ECG,- Electrograph; FFNN, Feed Forward Neural Network; FPN, Fusion of Paced and Normal Beat; PSO, Particle Swarm Optimization ;PVC, Premature Ventricular contraction; PCA, Principal Component Analysis; RMSE, Root Mean Square Error; SVM, Super Vector Machine; SVR, Super vector Regression.

I. INTRODUCTION

In recent year medical science technology has become widely increasing for automatic diagnosis of health problem. The electrocardiogram (ECG) plays a very significant role for diagnosing the health problem such as arrhythmia or other cardiac related issues. The purpose of ECG is to analyse and diagnoses the heart problem efficiently and accurately. The ECG receives the electrical signals from patient and obtains the arrhythmia signal information. In arrhythmia problem and genetic abnormalities change the contour of ECG signal; each portion of electrocardiogram beats contains information relevant to the doctor when a proper diagnosis is obtained.

The Fig. 1 shows the simple Electrocardiogram signal indicating the P, Q, R, S and T parameter [20]. The P beats occurs due to ventricular depolarization, the QRS are beats and the T beats due to ventricular depolarization. Volume of electrocardiogram ECG recorded in medical emergency is now increasing as heart disease patient are expanding at a disturbing rate.

The ECG signal contain various types of noise during the signal receives from patient such noise has some time high frequency or low frequency signal. It may affect the wrong diagnosis. So that noise removal is necessary.

As the technology changing researcher has been develop the many computational techniques or methods to extract the normal ECG signal from noisy data.

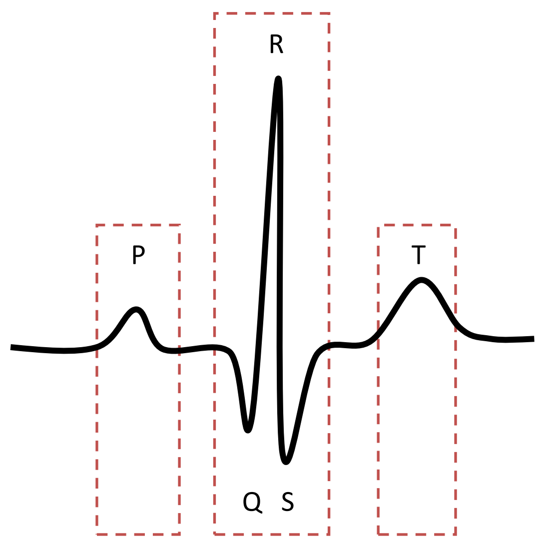

Fig. 1. Shows the simple Electrocardiogram signal.

In previous studies have been accomplished the various model of different kinds of feature extraction from ECG signals and a classification technique has been proposed. Feature extraction may contain the non-linear, time, frequency domain and multi domain feature extraction [2, 3]. For the classification classical methods is used such as Artificial Network, Support Vector Machine (SVM), Super vector regression (SVR) etc. In the time domain the ECG signal can be easily figure out by the noise and has low accuracy level [4, 5]. Another approach for extracting the ECG feature based on convolutional neural network model. The model has two sections; the first part extract the feature from ECG signals and second part perform the classification of feature based on the first section. Feature extraction was discussed based on principle component analysis to reduce the multidimensional data and input is processed by three pooling layer approach [6]. These signals cannot be consider as the accurate parameter of ECG signals for accomplishing high arrangement correctness. There are various combination of methods have been proposed for ECG feature extraction classification. For the feature optimization the genetic algorithm and the SVM based classifier designated for classification of ECG waveforms [7, 22, 23]. The Extreme learning machine algorithm calculates the minimum weight Single Hidden Layer Feed forward Neural Network for classification [8]. The KNN based approach for cardiac arrhythmia classification. The model is one of the types of recurrent neural network for classification is based on the LSTM in time serious domain. In the recent study, echo state network was implemented based on the morphology for classifying the normal and abnormal ECG signals of heart. The classification is based on the two classes SVEB and VEB [10]. The feature extraction from non-linear process in time and space domain based on the T complexity is applied to the RR and for classification used 13 different classes [11, 12].

Although, all above mentioned classification techniques or methods have good result, they used a combined space, time, frequency, linear and non-linear domain for ECG beat classification. So that present research proposed ECG waveform detection model that extracting the features in multi domain based on the empirical mode decomposition with linear discriminate analysis [13]. The combined approach of polyhedral conic separation and k-means clustering was applied as classifier to differentiate the ECG waveforms with 5 different classes such as N for Normal, RBBB for Right Bundle Branch Block, LBBB for Left Bundle Branch Block, APC for Atrial Premature Contraction and VPC for Ventricular Premature Contraction [14-15]. Kutlua and Kuntalp proposed a new cloud based model for automatic classification of ECG beats with minimum processing of signals [16]. The proposed model is based on the compression based similarity (CSM) and classification is done by KNN with one Bayesian classifier for better accuracy. An effective method to classify the ECG signal based on the super vector regression analysis on 400 samples of data set of various arrhythmias was proposed [24]. Proposed Model is tested and compared with the various neural network classifiers techniques and observed that it gives better accuracy than existing system. The purpose of this research is to propose an efficient arrhythmia detection techniques based on the kernel principle component analysis and support vector regression methods. In this research select 5 classes; normal Beat (N), Aberrant atrial premature Beats (S), Ventricular Ectopic beats (V), Combination beat (F), Unclassifiable beats (Q). We used Support vector regression classifier to classify the instances of ECG beats. In section II brief description of proposed methodology gives the data handling and signal pre-processing procedures. In section III and IV discusses the evaluation, result analysis and discussion and in section V conclusions.

II. PROPOSED METHODOLOGY

The entire schematic diagram of recommended model as present in Fig. 2. The Model based on the Kernel-PCA and SVR classifier for feature extraction and classification of ECG signal to detect the arrhythmia. First raw ECG signal is pre-processed using low pass filter to remove the noise after that applied Kernel-PCA and Higher Order Statistics method for feature extraction from ECG. The extracted feature is further processed for classification using the SVR algorithm.

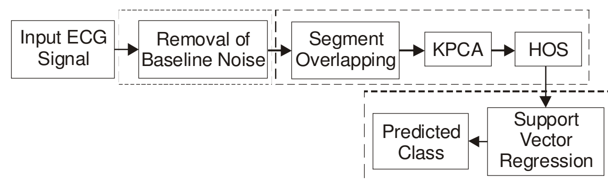

Fig. 2. Schematic diagram of Recommended Model for Classification of ECG signal.

Fig. 2 shows the proposed system can be categorized of three different sections such as pre-processing, obtaining feature and classification of beats. The working principle of proposed model as shown in following steps.

The raw ECG waveform are input to the system, and then pre-processed to remove the unwanted frequencies called as noise using the low pass filter.

Optimized the inputted ECG data by KPCA. KPCA is implemented to reduce the dimension and extract the ECG features. The wavelet transform techniques are used to extract the feature in frequency domain.

The KPCA are designated by non-linear and frequency domain parameter, which is useful for feature input to instruct and analyse the SVR classifier and finally predicted class of ECG signal, is classified from the MIT-BIH dataset.

A. ECG Signal pre-processing based on Low Pass Filter

The ECG beats are weak and it contains the noise so that pre-processing is required before the feature extraction [19]. Sometimes noise is distinct. We proposed the noise removal technique based on the low pass filter and pass the small frequency of ECG data and attenuates the high frequencies. Low pass filter function is proposed with cut-off frequency from 5 to 15Hz is used for noise removal is described below:

$$H(x_m, x_n) = \begin{cases} 1, & \sqrt{x_m^2 + x_n^2} \le X; \\ 0, & \sqrt{x_m^2 + x_n^2} > X. \end{cases} \tag{1}$$

where, X is the cut-off frequency

The Present techniques shows to verify the ECG Pre-processing. As adding the noisy data for pre-processing with the proposed techniques with 360 Hz interference.

$$RMSE = \left[\frac{1}{N}\sum_{i=0}^{n}(Y_i - \widehat{Y}_i)^2\right]^{\frac{1}{2}} \quad (2)$$

Where Y_i sample of ECG noisy signal, N is the sample length. ECG beat class from the dataset has been select for pre-processing by threshold.

B. Segmentation

The primary step is applied to show the lowest slope of ECG waveform such as goes down the waveform from R to S. and is also shows the higher slope of ECG waveform such as signal moving from lower Q to higher R.

$$y(x) = \frac{1}{2\Delta t}\big(y(x+1) - y(x-1)\big), \quad x = 0,\ 1,\ 2,\ 3 \dots\dots N-1 \quad (3)$$

Where, $2\Delta t$ for sample frequency and N for number of sample. Starting conditions are set to reduces error i.e., beginning condition is indicated for x = 0, and x - N-1.

C. KPCA for Feature Extraction

The ECG signal has uncertain amount of data and most of the significant data is incorporated into the nonlinear procedure. The non-linear process of feature extraction easier to finding out the normal ECG signals [20]. We present the KPCA method to extract the feature of ECG signals. The high-dimensional F-Space highlight (with measurement N) enables to acquire features (non-linear primary segments) with higher-request connections between information factors, and we can separate nonlinear segments up to n information point numbers (expecting n N). Portion PCA depends on standard direct PCA calculation in an element space where information x info is mapped by means of some non-linear capacity x [21]. Finally, we utilize part capacity to compute authorized location item in space.

First consider nonlinearly mapping all data points x to $f(x)$ in a higher dimensional feature space F. the covariance matrix can be estimated as

$$\sum f = \frac{1}{N}\sum_{n=1}^{N} f(X_n) f(X_n)^T \quad (4)$$

Plugging this into the eigen equation of the covariance matrix

$$\sum f\, \Phi_i = \lambda_i \Phi_i \quad (5)$$

Get the,

$$\left[\frac{1}{N}\sum_{n=1}^{N} f(X_n) f(X_n)^T\right]\Phi_i = \frac{1}{N}\sum_{n=1}^{N}(f(X_n)\,.\,\Phi_i) f(X_n) = \lambda_i \Phi_i \quad (6)$$

The eigen Φ_i vector is a linear combination of the N mapped data points

$$\Phi_i = \frac{1}{\lambda_i N}\sum_{n=1}^{N}(f(X_n)\,.\,\Phi_i) f(X_n) = \sum_{n=1}^{N} a_n^{(i)} f(X_n) \quad (7)$$

where, $a_n^{(i)} = \frac{1}{\lambda_i N}(f(X_n)\,.\,\Phi_i)$ (8)

Multiply $f(X_m)^T$ in equation 8 to both sides

$$(f(X_n)\,.\,\Phi_i) = \lambda_i N a_n^{(i)} = \sum_{n=1}^{N} a_n^{(i)} f(X_m)\,.\,f(X_n)) = \sum_{n=1}^{N} a_n^{(i)} k(X_m, X_n) \quad (9)$$

Where,

$$k(X_m, X_n) = ((X_m)\,.\,f(X_n)) \quad (m, n = 1 \dots\dots N) \quad (10)$$

Kernel representing a inner-product of two vectors in space F. If we consider $(m, n = 1 \dots\dots N)$

Equation 10 is scalar equation becomes the m-th component of the vector

$$\lambda_i N a_n^{(i)} = K a_i \quad (11)$$

Where, N is eigen vectors of K, which is obtained by solve the eigen value of K. The eigen value of K is proportional to eigen value of λ_i of the converiance matrix $\sum f$ for the feature selection of ECG beats in high dimensional space.

D. Higher Order System (HOS)

Depending upon the types of cardiac arrhythmia the ECG signals has some variation in shape. The proposed techniques should receive and eliminates these differences of signals. The cumulants are the good statistical function to eliminate the differences of ECG signals [18]. The normal signal amplitude varies from 1.15 to 1.36 which is same as the length of 0.39. The cumulant is a very powerful tool to reduce the error in ECG signals during the classification process [25]. The second, third and fourth order comulant are as follows:

$$\text{cumulant}(x_m,\ x_n) = E[x_m,\ x_n] \quad (12)$$

$$\text{cumulant}(x_m, x_n) = E[x_m, x_n, x_o] \quad (13)$$

$$\text{cumulant}(x_a, x_b, x_c, x_d) = E[x_m, x_n, x_o, x_p] - E[x_m, x_n]\, E[x_o, x_p] - E[x_m, x_o]\ E[x_n, x_p] - E[x_m, x_p]\, E[x_n, x_o] \quad (14)$$

Where, x_m, x_n, x_o, x_p is the Gaussian noise sequence independent from the data. Every order of function has certain feature. Where the second order function is signal variance, third order function is signal skewness and the fourth order function is signal kurtosis. These three functions disclose the HOS of ECG signals. This function can be used in combine the shows the classification result more accurately.

In our research, HOS gives the better result as compare the Gaussian noisy signal in ECG data. It is foreseen that higher order statistics could likewise eliminate the impact of other unwanted signals in cardiac arrhythmia dataset [25].

The length of the sample for feature extraction is the major problem in utilizing the higher order statistics. In our research, applied the KPCA model for sustain the shape of signals that shows the minimum length. So that by combining the HOS and KPCA to maintaining the morphology in proposed model.

E. SVR for Classification

After obtaining the feature of proposed model; each sample of ECG beats are classified individually based on the K-PCA and SVR. In this case each beat were not the same as the others, the most of the frequent output between the three component vectors as recent output.

Support Vector Regression (SVR): SVR is a Novel technique of learning system. This for solving supervised classification problems due to its generalization ability. In essence, SVM classifiers maximize the margin between training data and the decision boundary (optimal separating hyper plane), which can be formulated as a quadratic optimization problem in a feature space. The subset of patterns those are closest to the decision boundary are called as support vectors Regression. SVR uses undefined benchmarks from the SVM for gathering, with only two or three minor changes. As issue of first significance, since yield is a certified number it ends up being uncommonly difficult to foresee the present information, which has boundless possible results.

Because of backslide; an edge of obstruction (epsilon) is set in estimation to the SVM which would have adequately requested from the issue. However, other than this reality, there is in like manner an increasingly befuddled reason; the estimation is progressively tangled as such to be taken in thought.
Regardless, the rule thought is reliably the equivalent: to constrain botch, individualizing the hyper plane which enlarges the edge, recollecting that bit of the goof is persevered.
Kernel Function as
For Polynomial

$$k(x_m, x_n) = (x_m, x_n)^d \quad (15)$$

Where m, n is constant term and d is for degree of kernel. In equation 5 calculate the dot product of two vector term by increasing the power of kernel.
For Gaussian RBF

$$k(x_m, x_n) = \exp\left(-\frac{|x_m - x_n|^2}{2\sigma^2}\right) \quad (16)$$

$|x_m - x_n|$ is for Euclidean distance between x_m and x_n.
To determine the performance of proposed model of SVR classifier six parameters are used which is Sensitivity, Specificity, Accuracy, false positive rate, false negative rate and precision. All the parameters are calculated as follows.

$$\text{Specificity} = \frac{T\_P}{(T\_P + F\_N)} \quad (17)$$

$$\text{Sensitivity} = \frac{T\_N}{(T\_P + T\_P)} \quad (18)$$

$$\text{Accuracy} = (T\_P + T\_N)/(T\_P + F\_P + T\_N + F\_N) \quad (19)$$

$$FAR = (F\_P)/(F\_P + T\_N) \quad (20)$$

$$FRR = (F\_N)/(T\_P + F\_N) \quad (21)$$

$$\text{Precision} = (T\_P)/(T\_P + F\_P) \quad (22)$$

Where, T_P is for the True Positive, T_N is for True Negative, F_N is for False Negative, F_P is for False positive, FAR is for false positive rate and FRR is for false negative rate.

III. EVALUATION AND RESULT ANALYSIS

The proposed method characterizes the five different classes
ECG beat annotations:
N - beats starting in the sinus hub
S - Aberrant atrial premature Beats
V - Ventricular Ectopic beats
F - Combination beat
Q - Unclassifiable beats
In this Experimental analysis, the MIT/BIH arrhythmia database dataset is utilized for validate the proposed Method. The database contains comment for both planning data and beat class data checked by free specialists. A total of 1800 samples from the MIT-BIH arrhythmia database are equally divided into training sets. A total of 400 samples of N are derived from records 100, 101, 103 and 105. Similarly, 400 samples of APC are derived from records 109, 111, 207 and 214, and 400 samples of VFN are derived from records 118, 124, 212 and 231. We also derive 400 samples of PVC from records 106, 119, 200 and 203 and 200 samples of FPN from records 209 and 222. A total of 1800 samples are used as ECG data after sampling and pre-processing the ECG signals. It is suggested that every ECG beat be ordered into the accompanying five heartbeats composes: N, S, V, F and Q beats.

N-Beat. Normal ECG sample from MIT/BIH dataset is shown Fig. 3.

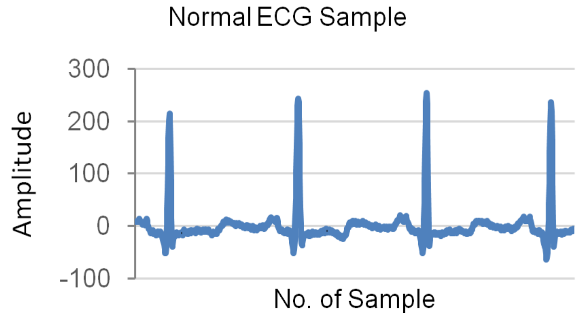

Fig. 3. N-beat ECG Sample.

Fig. 3 shows ECG signal to extract Time and Frequency based features. Those features are classified using SVR.

Table 1: Performance Analysis of Normal Class.

Parameter	Accuracy Level
Accuracy	0.9840
Sensitivity	0.92
Specificity	0.988571429
FAR	0.005747
FRR	0.148148
Precision	0.92

Table 1 shows the Performance Analysis of Normal Class. For Normal Class Total Accuracy for 100 randomly picked ECG sample of the MIT-BIH is 98.4 %. Below Figure shows the Accuracy, Sensitivity, Specificity, False Positive Rate, false Negative Rate and Precision.

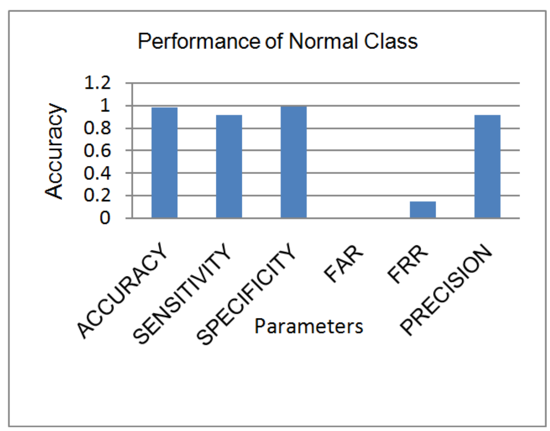

Fig. 4. Performance Analysis of N-beat Class.

S-Beat. Atrial premature complexes (APCs) are a common kind of heart arrhythmia characterized by premature heartbeats originating in the atria. Another name for atrial premature complexes is premature atrial contractions. When a premature beat occurs in the upper chambers of your heart, it’s known as an atrial complex or contraction. Premature beats can also occur in the lower chambers of your heart. These are known as ventricular complexes or contractions. Causes and symptoms of both types of premature beats are similar.
Fig. 5 shows the Aberrant atrial premature signal to extract the Time and frequency based feature and classify those feature using SVR.

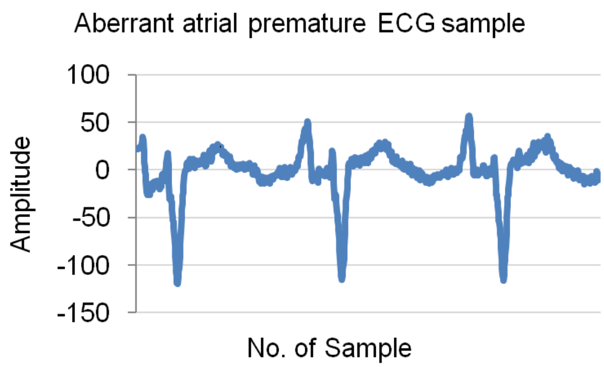

Fig. 5. Aberrant atrial premature ECG sample.

Table 2: Performance Analysis of Aberrant atrial premature Class.

Parameter	Accuracy Level
Accuracy	0.981333
Sensitivity	0.92
Specificity	0.985714
FAR	0.005764
FRR	0.178571
Precision	0.92

Table 2 shows Performance Analysis of Aberrant atrial premature Class. For Aberrant atrial premature Class Total Accuracy for 100 randomly picked ECG sample of the MIT-BIH dataset is 98.1 %.

Fig. 6 shows the performance analysis of S-beat with different parameter such as Accuracy, Sensitivity, Specificity, False Positive Rate, false Negative Rate and Precision.

V-Beat. Premature ventricular complexes/contractions (PVCs; also referred to a premature ventricular beats, premature ventricular depolarizations, or ventricular extra systoles) are triggered from the ventricular myocardium in a variety of situations. PVCs are common and occur in a broad spectrum of the population. Premature Ventricular Contraction ECG sample from combined dataset is shown Fig. 7.

Table 3 shows the Performance Analysis of Premature Ventricular Contraction Class. For Premature Ventricular Contraction Class Total Accuracy for 100 randomly picked ECG sample of the MIT-BIH data is 98.9 %.

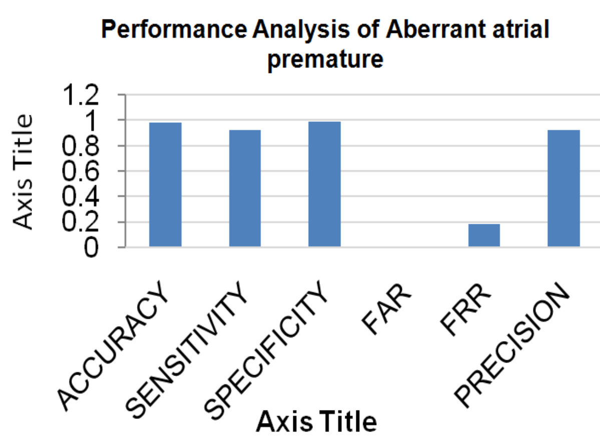

Fig. 6. Performance Analysis of S-Beat Class.

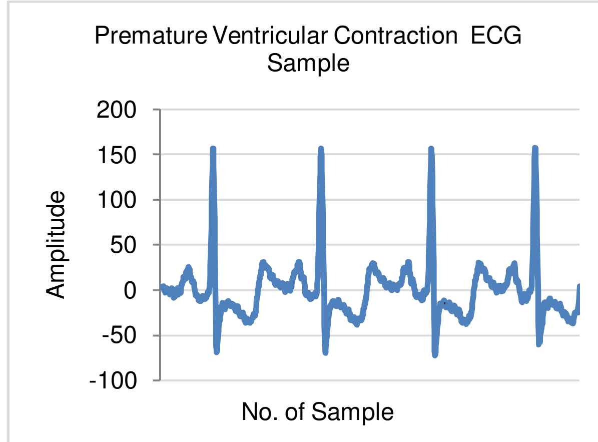

Fig. 7. V-beat class ECG Sample.

Table 3: Performance Analysis of Premature Ventricular Contraction Class.

Parameter	Accuracy Level
Accuracy	0.989333
Sensitivity	0.88
Specificity	0.997143
FAR	0.008523
FRR	0.043478
Precision	0.88

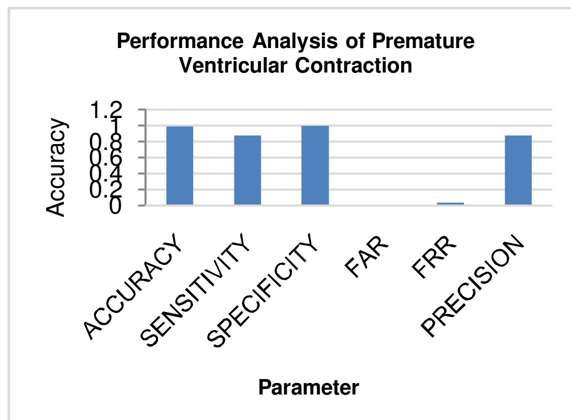

Fig. 8. Performance Analysis of V-beat class.

Fig. 8 shows the performance analysis of V-beat with different parameter such as Accuracy, Sensitivity, Specificity, False Positive Rate, false Negative Rate and Precision.

F-Beat. Combinational beat occurs when electrical impulses from different sources act upon the same region of the heart at the same time. If it acts upon the ventricular chambers it is called a ventricular combinational beat, whereas colliding currents in the atrial chambers produce atrial fusion beats. Ventricular combinational beats can occur when the heart's natural rhythm and the impulse from a pacemaker coincide to activate the same part of a ventricle at the same time, causing visible variation in configuration and height of the QRS complex of an electrocardiogram reading of the heart's activity. Combinational (Fusion) of ventricular and normal ECG sample from Combined dataset is shown Fig. 9.

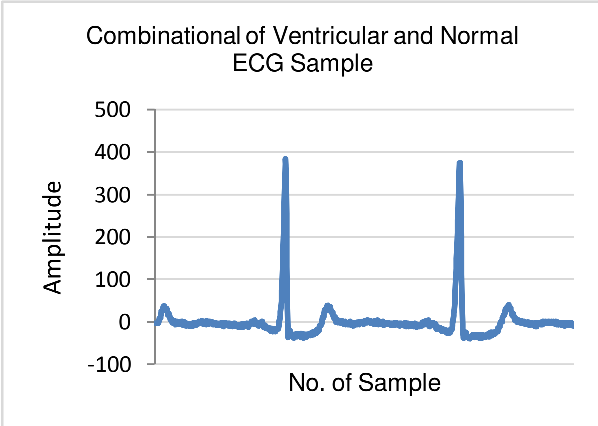

Fig. 9. Fusion of Ventricular and Normal ECG Sample.

Table 4: Performance Analysis of Fusion of Ventricular and Normal Class.

Parameter	Accuracy Level
Accuracy	0.986667
Sensitivity	0.88
Specificity	0.994286
FAR	0.008547
FRR	0.083333
Precision	0.88

Table 4 shows the Performance Analysis of Fusion of ventricular and normal Class. For Fusion of ventricular and normal Class Total Accuracy for 100 randomly picked ECG sample of the MIT-BIH data is 98.6 %.

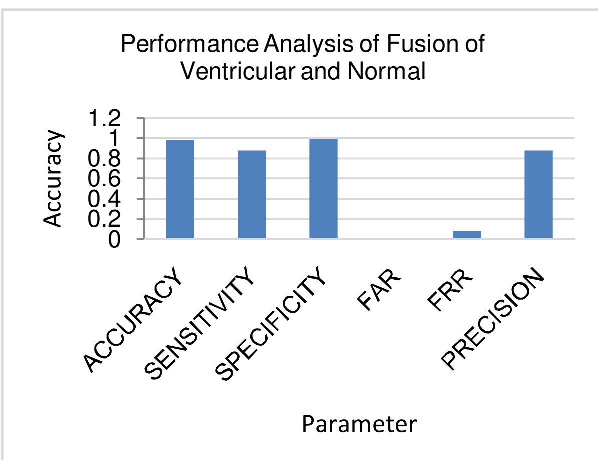

Fig. 10. Performance Analysis of F-Beat Class.

Fig. 10 shows the Performance Analysis of Fusion of ventricular and normal ECG beats such as Accuracy, Sensitivity, Specificity, False Positive Rate, false Negative Rate and Precision.

Q-Beats. Label that marks a segment of unreadable data. Unclassifiable ECG sample from combined dataset is shown in Fig. 11. Table 5 shows the Performance Analysis of Unclassifiable Class. For Unclassifiable Class Total Accuracy for 100 randomly picked ECG sample of the MIT-BIH data is 98.9 %.

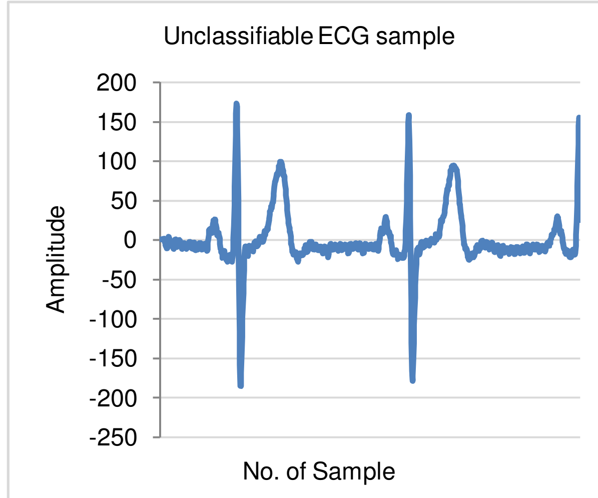

Fig. 11. Unclassifiable ECG sample.

Table 5: Performance Analysis of Unclassifiable Class.

Parameter	Accuracy Level
Accuracy	0.989333
Sensitivity	0.88
Specificity	0.997143
FAR	0.008523
FRR	0.043478
Precision	0.88

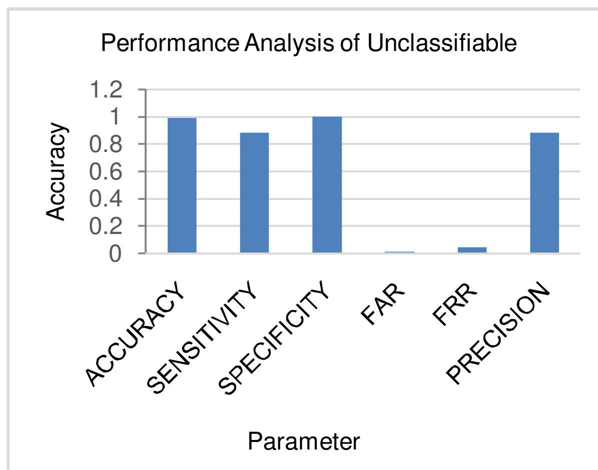

Fig. 12. Performance Analysis of Q-Beat Class.

Fig. 12 shows the Performance Analysis of Fusion of Unclassifiable ECG beats such as Accuracy, Sensitivity, Specificity, False Positive Rate, false Negative Rate and Precision. From Fig. 13 shows the comparing performance of several methods [1, 24, 26] with proposed KPCA-SVR method. It observed that specificity, sensitivity, positive prediction and false prediction rate of arrhythmia detection obtained by the suggested algorithm are better than the previous methods.

Table 6: Performance Evaluation of Several Methods and Proposed Methods.

Parameters	ANN	MD	SVM	KPCA-SVR
Sensitivity	0.93	0.98	0.94	0.98
Specificity	0.92	0.93	0.93	0.96
Positive Prediction	0.91	0.91	0.95	0.98
False Prediction	0.2	0.3	0.2	0.04

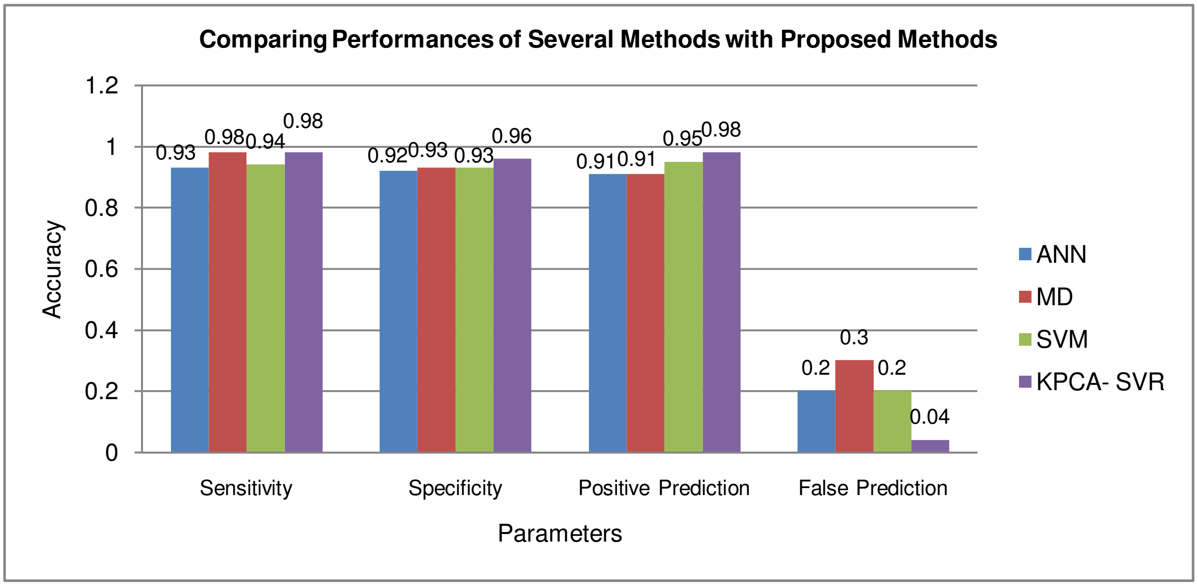

Fig. 13. Accuracy Comparisons of KPCA-SVR with other methods.

IV. RESULT AND DISCUSSION

Arrhythmia detection is an active research area in biomedical engineering with rapidly analysing the normalities and abnormalities of heart. The standard criteria for RR interval or ECG signal have number of limitations when discriminate the SVT from VT and alternative techniques have been suggested as the EGM width criterion which have the some limitation for QRS detection [10-13] and morphological techniques such as wavelet transform and Probability Density Function which do not have effective classification result [7, 22, 23]. The mechanism of feature extraction is proposed to extract the effective features for ECG recognition. The ECG data is sampled from MIT-BIH arrhythmia dataset and the data is pre-processed with low pass filter method with the 360 Hz interference. The various features have been proposed in the literature for classification of ECG beats. The classification performance of ECG beats is depends on feature extraction, feature reduction and classification algorithm. As the obtained results clearly indicate, ECG beats classification technique based on the combination of Kernel-PCA and SVR feature extraction to increase the accuracy, sensitivity, specificity and precision. This improvement can be caused by good performance of SVR classifier with reduced the number of ECG features.

V. CONCLUSION

In medical practices, computer based diagnosis of heart diseases or other kinds of heart problem can reduces the workload of medical practitioner and more concentrate on treatment rather than diagnosis. In this paper, an efficient Kernel-PCA and Support Vector Regression based ECG classification system is proposed to carry out automatic ECG arrhythmia detection by classify the patient's ECG into corresponding five kinds of cardiac arrhythmia condition such as Normal, Aberrant atrial premature, Ventricular Ectopic, Combination and Unclassifiable beats. Low pass filter method is used for pre-processing the ECG signal and removes the noise interference. The Proposed model uses the MIT-BIT cardiac arrhythmia dataset for ECG signal classification. The ECG signals have been classified into six common parameter are measure like Accuracy, sensitivity, specificity, False Positive Rate, false Negative Rate and Precision. The results show that the proposed algorithm is effective for prediction of cardiac arrhythmias, with an accuracy of 98%, sensitivity is 98%, Specificity is 96%, Positive Prediction is 98% and False Prediction is 0.4%. The proposed model can accomplish the better classification output so that diagnosis of cardiac arrhythmia effectively. The detection of arrhythmia by accuracy, specificity, sensitivity and prediction is superior to previous research because of the combination of KPCA and SVR in model. The higher order Statistics of cumulants are efficiently eliminates the variation in similar types of ECG signals so that easily classify the cardiac arrhythmia.

VI. FUTURE SCOPE

In our further research, we intend to focus on following points: (i) classification is performing on all the ECG beats of cardiac arrhythmia (ii) Optimal selection of feature sub-set to reduce the training time (computational requirements), (iii) achieving high classification accuracy with small sized input feature vector and limited training dataset.

Conflict of Interest. On behalf of all authors, the corresponding author states that there is no conflict of interest.

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