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Classification and analysis of cardiac arrhythmia based on incremental support vector regression on IOT platform

S.T. Sanamdikar [a,b,c,d,*], S.T. Hamde [a,b], V.G. Asutkar [a,b]

[a] Department of Instrumentation Engineering, Shri Guru Gobind Singhji Institute of Engineering and Technology, Nanded, India
[b] Swami Ramanand Teerth Marathawada University, Nanded, Maharashtra, India
[c] Department of Instrumentation and Control, PDEA College of Engineering, Manjari Budruk, Pune, India
[d] Savitribai Phule Pune University, Pune, Maharashtra, India

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ABSTRACT

The electrocardiogram (ECG) is a diagnostic device capable of monitoring normal or irregular heart function. The entire ECG beat can be categorized into five different forms of beat arrhythmias (N, S, V, F, U). Quick and precise diagnosis of forms of arrhythmia is critical for identifying the heart problem and provides the proper treatment to the patient. In this paper, Discrete Wavelet Transform and Higher Order Statistics techniques has been used for analyzing and determining the ECG signals and implement it on an IOT-based platform. This system is based on three categories: The first approach involves inputting the ECG data; the second approach involves extracting the ECG beats with their respective amplitude from the base line. Wavelet transform function, and higher order statistics are used to eliminate noise and unwanted signal components and thus to extract ECG features. The third approach is to classify the ECG beats based on the Incremental Support vector regression classifier. After classification ECG beat is transmitted to the controller section for signal processing are given to controller section (Arduino Uno). The process can be implemented by employing the statistical feature for the feature extraction from the ECG signal. Compared to other approaches, the method provided by Incremental Support vector regression to identify the ECG beats and predict arrhythmia can provide successful detection of arrhythmias. The basic concept of the proposed system is to provide patients with reliable health care by using cloud data compliance to allow doctors to use this information and to provide a fast and feasible service. The findings show that the proposed algorithm is successful in predicting cardiac arrhythmias, with a 98% that is higher than other approaches.

1. Introduction

Recognition of the ECG signal is very crucial in understanding the functioning of the heart as well as the diagnosis of heart disease under different circumstances. The American Heart Association stated in 2006 that 70 million people around the world face the cardiovascular disease problem. The basic reasons for Cardiovascular Disease (CVD) are hypertension, lacking physical exercise, ineffectively adjusted eating regimen, smoking and unusual glucose levels. Because of the existence of noise and heartbeat abnormality, physicians face complications in the Arrhythmias analysis [1,2]. In addition, visual inspection alone can result in a misdiagnosis or irrelevant detection of arrhythmias. Therefore, the computer aided analysis of ECG data supports physicians to proficiently detect arrhythmia. Arrhythmia is a cardiovascular condition that is caused by abnormal heart activity; electrocardiogram (ECG) is used to detect heart defects. Feature Extraction, selection and classification Construction are the three main steps in the detection of arrhythmias. The ECG beat classification [3] as per ANSI/AAMI EC57:1998 standard database shown in Table 1. In Feature extraction process the input data is transform into different of features for detecting heart diseases. The Purpose of this study is to evaluate the ECG beats classification performance with integrating two methods for feature extraction and evaluation using wavelet transformation and higher order statistics. The evaluation of ECG beats classification performance can be improved by using the incremental support vector regression.

The numerous models of different kinds of feature extraction from ECG signals were achieved in previous studies, and a classification technique was proposed. Feature extraction may contain the non-linear,

* Corresponding author.
E-mail address: sanamdikar123@gmail.com (S.T. Sanamdikar).

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Table 1
MIT-BIH arrhythmia beats classification per ANSI/AAMI EC57:1998 standard database [21–41].

AAMI classes	MIT-BIH heartbeat classes
Non-Ectopic Beat (N)	Normal Beat (N)
	Left Bundle Branch Block (LBBB)
	Right Bundle Branch Block (RBBB)
	Nodal Escape (j)
	Atrial Escape Beat (e)
Supra-Ventricular ectopic Beat (S)	Aberrated Atrial Premature Beat (A)
	Atrial Premature (a)
	Supraventricular premature (S)
	Nodal premature (J)
Ventricular ectopic Beat (V)	Ventricular Escape (V)
	Premature ventricular contraction (E)
Fusion Beat (F)	Fusion of ventricular and normal (F)
Unknown Beat (U)	Unclassifiable (U)
	paced (p)
	Fusion of paced and normal (f)

time, frequency domain and multi domain feature extraction [3,4]. For the classification classical methods is used such as Artificial Network, Support Vector Machine (SVM), Super vector regression (SVR) etc. The ECG signal can be easily identified by the noise in the time domain and has a low accuracy level [5,6]. 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 [7]. These signals cannot be considered as the accurate parameter of ECG signals for accomplishing high arrangement correctness. There are various combinations of methods proposed for classification of the ECG feature extraction. The genetic algorithm and SVM-based classifier designated for the classification of ECG waveforms [8–24] are used for the function optimization. The Extreme learning machine algorithm calculates the minimum weight Single Hidden Layer Feed Forward Neural Network for classification [9]. 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 extraction of features from non-linear method in the time and space domain based on the T complexity is applied to the RR and 13 different classes are used for classification [11,12].

Although the above mentioned techniques or methods of classification have good results, they used a combined space, time, frequency, linear and non-linear domain for beat classification of the ECG. This research suggests an ECG waveform detection model that extracts multi-domain features based on empirical mode of decomposition with linear discriminatory analysis [13,14]. 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 [15–18]. Ref [19] proposed a new cloud based model for automatic classification of ECG beats with minimum processing of signals. HOS and DWT is used for classify the ECG beats based on multivariate analysis [20–23]. The classification is performed based on feed forward neural network machine learning technique and particle swarm optimization [22] An effective method to classify the ECG signal based on the support vector regression analysis on 400 samples of data set of various arrhythmias was proposed [24,25]. The KPCA-SVR approach was used for detecting the cardiac arrhythmia [35]. The proposed model is evaluated and compared with the different techniques of neural network classifiers, and found that it offers better accuracy than the current method.

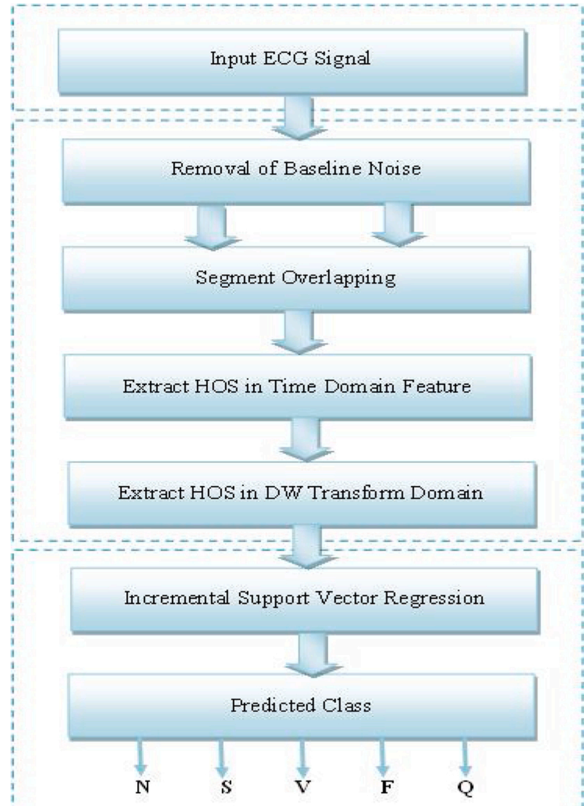

Fig. 1. The three tier architecture for recognition and classification of ECG signal for cardiac arrhythmia system.

2. Proposed methodology

Fig. 1 shows the three tier architecture of research work. The System consists of three sections such as input ECG signal, feature extraction and classification. The ECG beats are derived using the discrete wavelet transform and higher order statistics. These non-linear techniques have been used to extract the ECG beats better than others because of their versatility. In the Discrete Wavelet Transform and higher order statistics, the original ECG signal is decomposed in the time domain to remove the low-frequency component to eliminate the baseline and eliminate the high-frequency component to remove the noise and extract the function in the ECG signals. Sample frequency of ECG signal is 360 Hz. In the final step, classification is carried out on the extracted function of ECG beats and decides normal and abnormal arrhythmia activities. After classification of ECG beats sent to the IOT cloud. It is suitable for 24 × 7 monitoring of the patient. In almost all cases, the classification accuracy achieved is above 98%. The key purpose of the new scheme is to provide patients with safer and more effective services by creating a registry of collective records so that practitioners and physicians can use this database to provide evidence and an effective cure for arrhythmia. The execution times we acquired from actualizing the application on the ATMEGA328 P Microcontroller demonstrate that the ECG investigation and characterization can be performed progressively. TCP/IP protocol is used to transfer the data from controller section to remote hospital. Basically two steps for designing a programming logic one for receiving the signal and another is transmitting the signal using TCP/IP protocol. Set an integer number to packet data; be certain that the information is sent without misfortune of data. Heart beat is never transmitted to the base station (Controller) when heart beat is normal. Where the irregular condition is found. The transmitter is turned on and transmits data about heart beat to remote hospital.

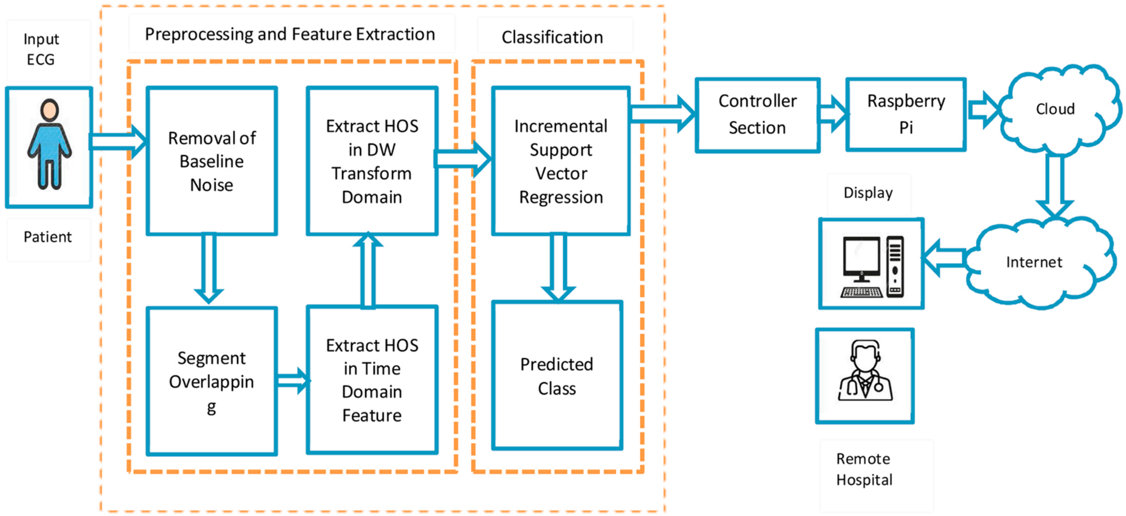

Fig. 2. Complete architecture of proposed model with IOT Platform.

2.1. *Signal preprocessing*

2.1.1. *Removal of baseline noise*

Baseline signal noise has an effect on normal ECG [2]. Noise frequency from around 0.5 to 0.6 Hz. Used high pass filter with the cut-off frequency 0.5 to 0.6 Hz [3,4] to eliminate such noise in signal. If the physical activity of the patient's body increases, then the frequency parameter of the baseline [26–28] increases such that the baseline noise signal is a low signal and a high pass filter with a cut-off frequency of 0.5 to 0.6 Hz is used to eliminate the baseline noise in the ECG signal.

2.1.2. *Discrete wavelet transform function*

In ECG signals consists of variety signals i.e. noise and it is required to remove the undesirable signals and extract useful feature from ECG. So many researchers have developed effective techniques for extracting the important feature for EEG and ECG signals based on the wavelet transform. In this section we will discuss the discrete wavelet transform function in time domain feature with the respective signal shape.

For the feature extraction, we acquire the concept of Yakup Kutlu and Damla Kuntalp [36] studied the wavelet and HOS techniques for noise removal. They proposed the good techniques for noise removal which gives the better result of noise removal as compare to others [27].

The signal is divided into the two parts High and Low frequencies.

The Low frequency again divided into two parts high and low frequency. This process is continued until the signal has been entirely decomposed.

$$y_{high}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n+1-k] \quad (1)$$

$$y_{low}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k] \quad (2)$$

Where,

$x[k]$ is input ECG signal

$g[n]$ and $h[n]$ is Impulse response of high pass filter

There is n +1 possibility to encrypt ECG signal for the n level decomposition. Noise is removed from ECG signal using low and high pass filter. In wavelet transformation, approximate precise coefficient is just like binary tree. Such decomposition is applied on low and high frequencies. And again cerate next level of tree, make 2^{2n-1} in various way to encrypt the ECG signal. Each n level, there is 2^{n-1} nodes. The wavelet decomposition can be obtained at fourth level that means data in fourth level is used to extract the feature.

2.1.3. *Higher order statistics*

The higher order statistics (HOS) has importance in bio-medical signal processing field but first and second order statistics are not sufficient for all the representing it. So that we used third and fourth order statistics for analysis.

2.1.4. *Statistical features*

For evaluating the feature decomposition of signal is an important step in signal processing. In our proposed scheme we are evaluating some statistical feature such as energy, mean, median, entropy, standard deviation, skewness, kurtosis, covariance and to create feature set [29, 30]. The entire feature is evaluated in MATLAB software. Following are the standard equations used for evaluating feature based on C_{ab} at 4th level of decomposition

Following features are a set of statistical parameters to measure a distribution,

$$\boldsymbol{Energy} = \sum_{i=1}^{n} C_{ab}^{2} \quad (3)$$

Standard Deviation

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2} \quad (4)$$

Mean

$$M = \frac{1}{N}\sum_{i=1}^{N-1} A_i \quad (5)$$

2.1.4.1. *Kurtosis.*

used to measure the data sharpness is peaked from ECG signal. In data set A_1, A_2, A_n

$$KUR = \frac{\sum_{i=1}^{n}(A_i-\overline{A})}{N}/SD4 \quad (6)$$

Where, $\overline{A}$-mean, N-number of data points, SD-standard deviation

Skewness

$$SK = \frac{\varepsilon(C_{ab}-\mu a)^3}{\sigma_a^3} \quad (7)$$

The coefficients C_{ab} is the decomposition coefficient. Here i = 1, 2, …,i is the node number at 4th level of decomposition. N is the number of coefficients at the coefficients C_{ab} is the decomposition coefficient. Here i = 1,2,…,l is the node number at 4th level of decomposition. N is the number of coefficients.

2.1.5. RR interval features

We have picked RR interim data as the main time space includes in our investigation. Two RR interims are figured straightforwardly from the R areas named as past RR and post RR interims. Past RR is characterized as the time remove among present and past R area while post RR is the time separate between current R area and the accompanying one [31].

- Past RR, (RR_i): The interval between ith R beat and past R beat.
- Post RR $RR_{(i+1)}$: interval between ith R beat to next R beat.
- Average of RR interval in 1-min, (RR_i): Averaged RR interval of 1-min of ECG
- Average 20-min RR interval, (RR_{20}): average RR interval of 20-min ECG

3. ECG beat classification model

This section describes the ISVR classifier used for the ECG beats classification.

3.1. ISVR classifier

The Incremental Support Vector Regression (ISVR) utilizes indistinguishable working standards from the SVM for grouping, with just a couple of minor contrasts. As a matter of first importance, since yield is a genuine number it turns out to be extremely hard to anticipate the current data, which has vast prospects. On account of relapse, an edge of resistance (epsilon) is set in estimate to the SVM which would have just mentioned from the issue. In any case, other than this reality, there is additionally an increasingly confused explanation; the calculation is progressively entangled subsequently to be taken in thought. In any case, the primary thought is consistently the equivalent: to limit mistake, individualizing the hyper plane which expands the edge, remembering that piece of the blunder is endured [32]. In this research Incremental SVR approach is used to develop the regression model. The training data are delivered to adjust the proposed model parameters, at the same time as the take a look at data are used to evaluating the prediction accuracy of the proposed model.

The complete description of ISVR techniques are given below.

(1) Load the data set.
(2) Data set can be placed in multi-dimensional function space and the data can be determined based on kernel function.
(3) To search the linear relationship of data in multi-dimensional space to find another hyper-plan with large vector.

Primarily, ISVR select the hyper-plan with maximum vector value between plan and both positive/negative points. Selection of Optimal hyper-plan is based on distance between data points and hyper-plan is maximum known as support vector.

Given training data set (a_1, b_1), …… (a_n, b_n), $p_i \in \{-11\}$ So we required to learn optimal hyper-plan $w.a + y = 0$, with max margin equivalent to decision function $f(x) = sign(w.a + y)$

The objective function,

Max

$$\varnothing(w) = \frac{1}{2}\|w\|^2 \rightarrow \dot{min} \tag{8}$$

ST constraint

$$p_i\,(w^t \,.\, a_i y) \geq 1,\; i = 1, 2, \ldots..N \tag{9}$$

The above Eq. (10) can be change into optimization problem so that can be solved by Lagrange multiplier technique.

$$\begin{cases} L(w,\ y, \alpha) = \dfrac{1}{2}\|w\|^2 - \displaystyle\sum_{i=1}^{N} \propto_i (p_i(w.a_i + y) - 1) \rightarrow \begin{matrix} \min \ max \\ w, y \quad \propto \end{matrix} \\ \propto_i\ \geq 0,\ i = 1, 2, 3, \ldots\ldots N \end{cases} \tag{10}$$

Apply partial derivatives with respect to w and y and we will get,

$$\begin{cases} \dfrac{\partial}{\partial w} L(w, y, \propto) = 0 \Rightarrow w = \displaystyle\sum_{i=1}^{N} \propto_i,\ p_i,\ a_i \\ \dfrac{\partial}{\partial y} L(w, y, \propto) = 0 \Longrightarrow \displaystyle\sum_{i=1}^{N} \propto_i, p_i \end{cases} \tag{11}$$

Adding Eq. (12) into Eq. (11) and removes the variables w and y and we get dual optimization problem

$$\begin{cases} Q(\propto) = \displaystyle\sum_{i=1}^{N} \propto_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \propto_i \propto_j p_i p_j a_i a_{j \rightarrow} \ \begin{matrix} max \\ \propto \end{matrix} \\ \propto_i \geq 0\ \forall\ i = 1,\ \ldots\ldots.N \ and \ \displaystyle\sum_{i=1}^{N} \propto_i p_i \end{cases} \tag{12}$$

If input data is not linearly distinguishable, to find min. value,

$$\varnothing(w) = \frac{1}{2} w^t.\ w + C\sum_{i=1}^{N} \xi_i \rightarrow \begin{matrix} min \\ w, y, \xi \end{matrix} \tag{13}$$

ξ *is slack variable* It can be used for classification error and also minimized. C is user defined penalty variable. Final function is as follows;

$$w = \sum_{i=1}^{k} \propto_i p_i a_i \tag{14}$$

It also written as,

$$f(x) = sign\left(\sum_{i=0}^{N} \propto_i p_i (a^t.a_i) + y\right) \tag{15}$$

The Eq. (16) shows the dot product two variables known as training and testing data set. Presents the kernel function to integrate the sample data with proposed mapping function [39]. Final function can be written as,

$$f(x) = sign\left(\sum_{i=0}^{N} \propto_i p_i \varnothing(a^t)\ .\ \varnothing(a_i) + y\right)$$

$$= sign\left(\sum_{i=0}^{N} \propto_i y_i F(a^t a_i) + b\right) \tag{16}$$

The Eq. (17) shows the kernel function $F(a^t a_i)$. Our kernel function for proposed ISVR technique is as follows;

$$F(a^t a_i) = \exp(-\gamma\,\|a^t - a_i\|^2) \tag{17}$$

Above Eq. (17) will be used in proposed classification which has better classification accuracy.

To determine the performance of proposed model of ISVR 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.

$$Sensitivity = \frac{T\_P}{(T\_P + F\_N)} \tag{18}$$

Table 2
Classify the MIT/BIH arrhythmia dataset into training sets.

Beat	Class	Records	Total
N	N	100, 101, 103, 105	400
S	SVP	109, 111, 207, 214	400
V	PVC	118, 124, 212, 231	400
F	VFN	106, 119, 200, 203	400
Q	FPN	209, 222	200
Total			**1800**

$$Specificity = \frac{T\_N}{(T\_N + F\_P)} \quad (19)$$

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

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

$$FRR = (F\_N)/(T\_P + F\_N) \quad (22)$$

$$Precision = (T\_P)/(T\_P + F\_P) \quad (23)$$

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.

4. IOT platform

In Fig. 2, display the complete system architecture but in this section it presents the functioning of IOT in the framework proposed.

4.1. Hardware used

4.1.1. Data acquisition

The ECG signal is integrated with the circuit and used to amplify and filter ECG signal. CE 8232 is used for data acquisition connected to Arduino of ADC pins with 2.0 V to 3.5 V operational voltage.

4.1.2. Raspberry pi

The small sized raspberry pi is used with high specification in our proposed IOT based model. It has a core processor 32 bit 40 pin Quad with speed of 900 MHz. It has 4 USB port, 1 GB of memory (RAM), Ethernet port, and micro-SD port to store the OS and other files, and 5 V, 2A to run low power consumption.

4.1.3. Arduino uno

microcontroller with 16 MHz clock frequency, 14 I/O pins, USB Port, and power supply. It has 10-bit ADC to digitize the ECG signals and transfer to Raspberry pi with sample rate 860 sps (samples per second). The Inter-Integrated Circuit (I2C) protocol is used for data transfer.

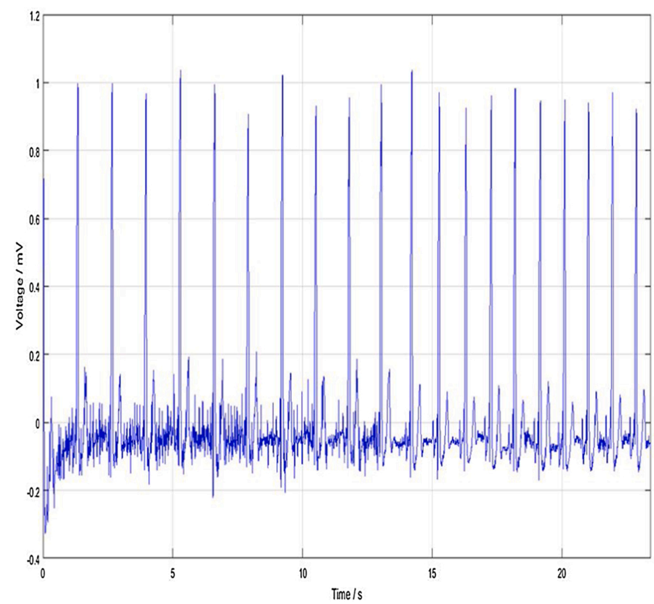

Fig. 4. Supra-ventricular premature ECG sample.

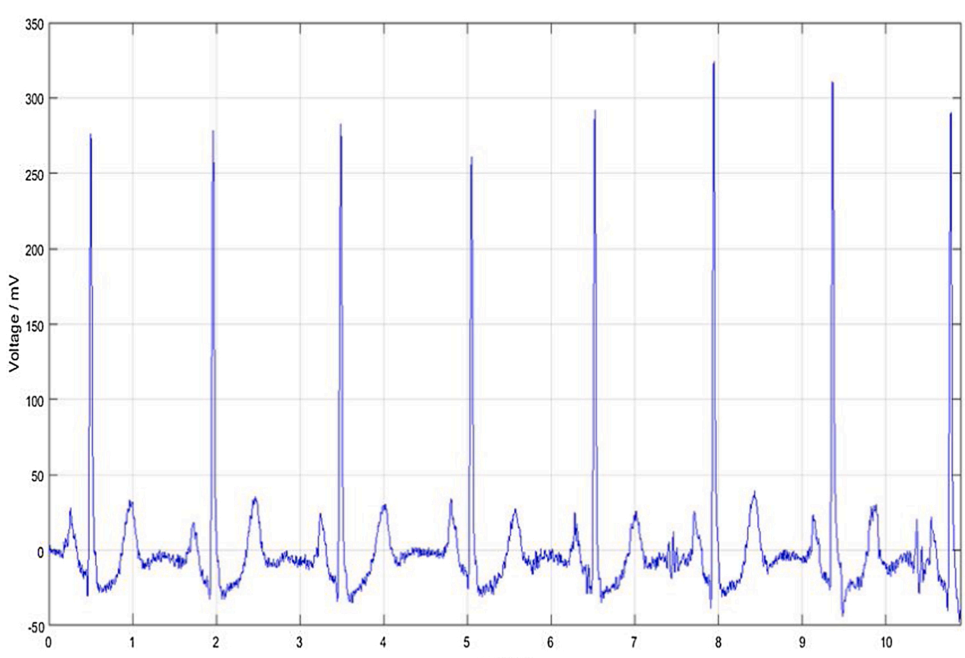

Fig. 3. Normal ECG sample.

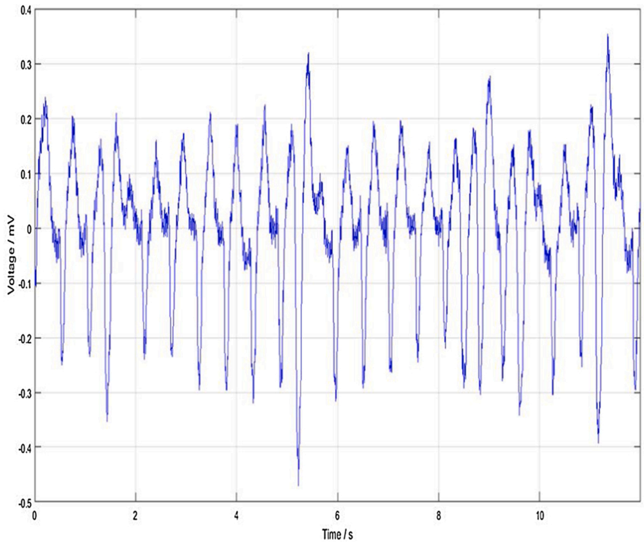

Fig. 5. Premature ventricular contraction ECG Sample.

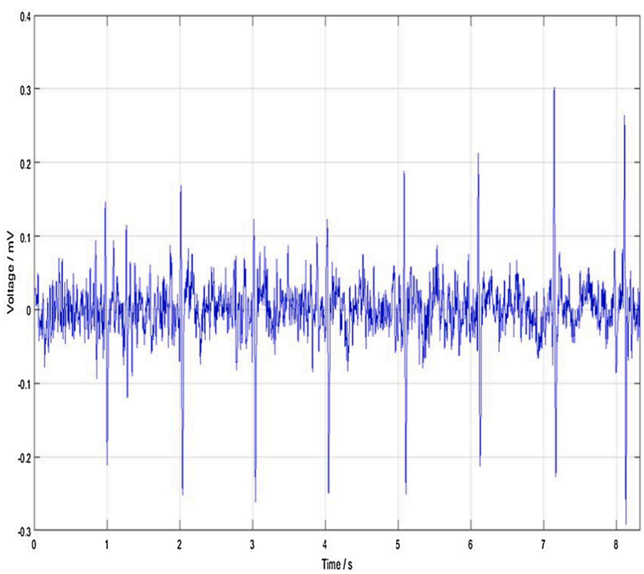

Fig. 6. Fusion of ventricular and normal ECG sample.

4.2. Controller section

In this section, the signals coming from the signal processing section are given to controller section (Arduino Uno). Arduino Uno has been used for converting analog signal to digital signal [33,34]. The data is coming from the sensor and sent to Raspberry from Arduino Uno. For the internet connectivity, Wi-Fi Modem is connected to the Raspberry Pi and data is stored to the cloud as the Raspberry Pi is registered to the cloud [36–38].

4.3. IOT cloud

The ECG signals are the transition of Wi-Fi linked to the Raspberry Pi from Raspberry Pi into the cloud. Data authorization, identity procedure has been ensured in such a way that the most effective authorized character would have access to the data of the person concerned [32]. ECG beats can be plotted for remote hospital doctor to view processing section.

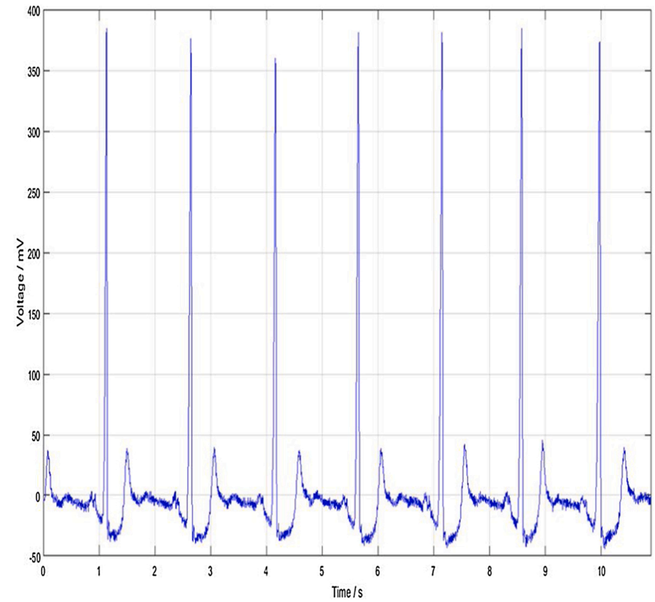

Fig. 7. Fusion of paced and normal ECG sample.

5. Result analysis

The proposed method characterizes the five different classes
ECG beat annotations:
N - Normal
S - Supraventricular Ectopic Beats
V - Ventricular Ectopic beats
F - Fusion of ventricular and normal
Q - Fusion of Paced and Normal
In this Experimental analysis, the MIT/BIH arrhythmia dataset is utilized for validate the proposed Method. The database contains comment for both planning data and beat class data checked by free specialists. This dataset to create a five different beats categories in according to the Association for the advancement of Medical Instrumentation (AAMI) [21–41]. The Table 1 represents the summary of mapping beat classification per ANSI/AAMI EC57:1998 standard database. The Complete MIT-BIH arrhythmia dataset has been classified into 1800 samples of training sets as shown in Table 2.

Table 2 shows the record. Each record has unique number and this number shows the specific set of characteristics of ECG [40]. N class for 400 samples is obtained from 100, 101, 103 and 105 records. For APC class, 400 samples are obtained from 109, 111, 207 and 214 records. For VFN class, 400 samples of are obtained from 118, 124, 212 and 231 records. For PVC class, 400 samples are obtained from 106, 119, 200 and 203 records. Finally, for FPN class 200 samples are obtained from 209 and 222 records.

Following the sampling and pre-processing of ECG signals a complete of 1800 samples of ECG beats is needed. It is proposed that each ECG beat be grouped into the five heartbeats accompanying it composes: N S, V F, and Q beats.

5.1. N: normal

From Fig. 3, ECG signals we extract Time and Frequency based features. Those features are classified using ISVR.

5.1.1. S-Beat

Supraventricular untimely beats speak to untimely actuation of the atria from a site other than the sinus hub and can begin from the atria or the atrio ventricular hub (called junctional untimely beats), however by far most are atrial in cause.

Table 3
Performance analysis of ECG beats.

Class	Accuracy	Sensitivity	Specificity	FAR	FRR	Precision
N-Normal	0.984000	0.92	0.988571	0.005747	0.148148	0.92
S-SVP	0.986667	0.88	0.994286	0.008547	0.083333	0.88
V-PVC	0.989333	0.88	0.997143	0.008523	0.043478	0.88
F-VFN	0.986667	0.88	0.994286	0.008547	0.083333	0.88
Q-FPN	0.986667	0.88	0.994286	0.008547	0.083333	0.88

Table 4
Time domain feature.

Class	F1 Mean	F2 Variance	F3 Std. deviation	F4 Skewness	F5 Kurtosis	F6 Inst amplitude	F7 Range	F8 Modulated amplitude	F9 Max freq	F10 RR interval
N-Normal	0.00070	1283.5	35.826	5.0614	33.494	0.0290	777.01	4.17e+08	1189.10	257.87
S-SVP	0.00153	4458.62	66.772	3.4610	18.043	0.0237	624.14	1.45E+09	7635.45	344.37
V-PVC	0.00037	1080.72	32.874	1.7510	10.391	0.0062	354.19	3.51E+08	4162.32	260.62
F-VFN	4.7E-05	4072.35	63.814	4.0384	24.124	0.0059	985.05	1.32E+09	3688.40	270.00
Q-FPN	0.00120	10189.7	100.94	3.9727	22.174	0.2092	1333.90	3.31E+09	11400.3	259.62

Fig. 4 shows the Supra-Ventricular Premature signal to extract the Time and frequency based feature and classify those feature using ISVR.

5.1.2. V-Beat

Premature ventricular complexes/contractions (PVCs; also referred to a premature ventricular beats, premature ventricular depolarization, 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. 5.

Fig. 5 shows the Premature ventricular contraction signal to extract the Time and frequency based feature and classify those feature using ISVR.

5.1.3. F: Fusion of ventricular and normal

A fusion beat occurs at the point when electrical driving forces from various sources follow up on a similar area of the heart simultaneously. In the event that it follows up on the ventricular chambers it is known as a ventricular combination beat, while impacting flows in the atrial chambers produce atrial combination beats.

Fig. 6 shows the Fusion of Ventricular and Normal signal to extract the Time and frequency based feature and classify those feature using ISVR.

5.1.4. Q: fusion of paced and normal

A pacemaker combination beat happens when the natural beat and pacemaker improvement beat somewhat depolarize the ventricles a hybrid QRS complex.

Fig. 7 shows the Fusion of Paced and Normal signal to extract the Time and frequency based feature and classify those feature using ISVR.

5.2. Performance analysis classes

Table 3 shows the comparing performance of ECG beats based on proposed ISVR method. The result shows that specificity, sensitivity, positive prediction and false prediction rate of arrhythmia detection obtained better results by the suggested method. While accuracy measures the overall system performance over the selected classes of beats, the other metrics are specific to each class and they measure the ability of the classification algorithm.

5.3. Time domain feature vector

Table 4 shows estimate the various feature of ECG beats in time domain vector.

5.4. Frequency domain feature vector

Table 5 shows estimate the various feature of ECG beats in frequency domain vector.

In this investigation observed in other useful fields i.e. Incremental SVR based on the Wavelet transform and HOS as compared to various classifiers that deal with feature space of large dimensionality. The Table 6 shows the various classifier accuracies result with the proposed ISVR classifier. The overall accuracies achieved with the proposed ISVR classifier are equal to 98%. This result is better than those achieved by the GSNN, KPCA-SVR and SVM. Comparison of the proposed systems built in this research with similar systems work in literature is a tedious task because each author used different methods of classification, types of arrhythmia, classification of arrhythmia, types of dataset and system performance. Fig. 8 demonstrates the comparative study of the method proposed with other classifier techniques. All the techniques for the classification were working well. The best performance of accuracy in classification is calculated using an ISVR method [35,42].

6. Discussion

A few investigations have tended to this issue by presenting various strategies. Berdakh Abibullaev et al. (2010) has recognized an approach for detection and classification of cardiac arrhythmias based on SVM but this research work has indicated less accuracy as compare to our proposed scheme with regards to the classification of cardiovascular arrhythmias except if they are constrained in light of the utilization of SVM. Miquel Alfaras et al. (2019) propose a technique for fast ECG arrhythmia classification based on machine learning from MIT-BIH database used for classification but has not applicable to real-time application. Yakup Kutlu et al. (2012) describes feature extraction based on the HOS and wavelet transforms techniques. The performance accuracy is measured based on the sensitivity, specificity and selectivity of 90%, 92% and 98% respectively. But the outcomes show up extremely constrained contrasted with the professional requirements for arrhythmia recognition. This Stage our work doesn't have impediments in examined information presented a statistical features and the created symptomatic methodology has a few favorable circumstances in contrast with past works.

The feature extraction mechanism is proposed to extract the effective features for ECG recognition and to implement for continuous patient monitoring on the IOT-based platform. The ECG data is sampled from the MIT-BIH arrhythmia dataset and the data is pre-processed with cut-off frequency using high pass filter. The various features for classifying ECG beats have been proposed in the literature. The classification

Table 5
Frequency domain feature.

Class	F11 Wavelet Mean	F12 Wavelet Variance	F13 Std. deviation	F14 Wavelet Skew	F15 Wavelet Kurtosis	F16 Inst amplitude	F17 Wave Range	F18 Modulated amplitude	F19 Max freq	F20 Wavelet Energy
N-Normal	0.1800	7924.70	89.020	0.9939	15.320	1.03e-06	1063.9	1.63e+08	330.71	3.7e+09
S-SVP	0.0015	4458.62	66.77295	3.4610	18.04385	0.02379	624.1	1.45E+09	7635.45	344.375
V-PVC	0.4413	5004.94	70.745	0.2638	12.098	2.18E-08	781.6	1.01E+08	329.30	2.2E+09
F-VFN	0.2552	11438.50	106.95	0.4824	17.456	3.83E-07	1404.4	2.34E+08	621.01	5.5E+09
Q-FPN	0.1998	41872.10	204.62	0.2503	16.141	5.42E-08	2360.8	8.41E+08	1860.10	2.2E+10

Table 6
Accuracy of different classifier.

Class	ISVR	SVM	GSNN	KPCA-SVR
N-Normal	98.4000	95.4167	98.2200	97.4000
S-SVP	98.6667	94.1667	96.3300	96.1300
V-PVC	98.9333	94.5833	98.2100	97.9300
F-VFN	98.6667	94.5833	97.2400	97.9600
Q-FPN	98.6667	94.5833	98.2300	93.9300

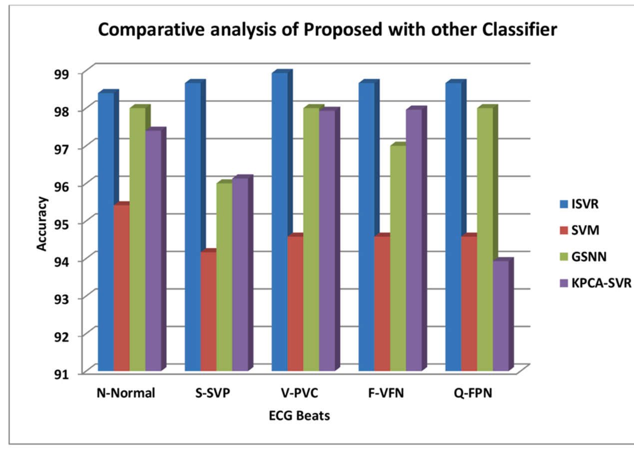

Fig. 8. Graphical representation of proposed ISVR classifier with other classifier.

performance of ECG beats depends on the extraction of features, the reduction of features and the algorithm for classification. As the results obtained clearly indicate, ECG beats classification technique based on Incremental SVR feature extraction to improve accuracy, sensitivity, specificity and precision. This improvement may be caused by good Incremental SVR classifier performance.

7. Conclusion

In this paper the Incremental support vector regression based on wavelet and HOS can be effectively applied and to achieve a reasonable degree of accuracy for the detection of cardiac arrhythmia. An efficient Incremental 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, Supraventricular Ectopic, Ventricular Ectopic, Fusion of ventricular and normal and Fusion of Paced and Normal beats and implement it on an IOT based embedded platform. For pre-processing the ECG signal, the high pass filter with the cut-off frequency 0.5 to 0.6 Hz is used and the noise interference is reduced. The proposed model uses the cardiac arrhythmia dataset MIT-BIT for the classification of the ECG signals. ISVR classifier efficiency is calculated by their accuracy, sensitivity, specificity, False Positive Rate, False Negative Rate and Precision. We also estimate some statistical feature in time and frequency domain. The findings show that the proposed algorithm is successful in predicting cardiac arrhythmias, with a 98% that is higher than other approaches. The basic idea of the proposed framework is to give patients better and better welfare administrations by executing cloud system data with the goal that the specialists use this information and provide a quick and productive solution.

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Credit author statement

This research paper is written, implemented, designed software and hardware etc are done by all three authors equally. we are all three responsible for this paper.

Declaration of Competing Interest

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

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at https://doi.org/10.1016/j.bspc.2020.102324.

References

[1] Berdakh Abibullaev, Won-Seok Kang, Seung Hyun Lee, Jinung an, Classification of cardiac arrhythmias using biorthogonal wavelets and support vector machines, Int. J. Adv. Comput. Technol. 2 (June (2)) (2010).

[2] Padmavathi Kora, K. Sri Rama Krishna, ECG based heart arrhythmia detection using wavelet coherence and Bat algorithm, Sensing Imaging 17 (June (1)) (2016).

[3] Gustavo Lenis, Nicolas Pilia, Axel Loewe, Walther H.W. Schulze, Olaf Dössel, Comparison of baseline wander removal techniques considering the preservation of ST changes in the ischemic ECG: a simulation study, Comput. Math. Methods Med. (2017), 9295029, https://doi.org/10.1155/2017/9295029. Hindawi. 13 pages.

[4] N. Maglaveras, T. Stamkapoulos, K. Diamantaras, C. Pappas, M. Strintzis, ECG pattern recognition and classification using nonlinear transformations and neural networks: a review, Int. J. Med. Inform. 52 (1998) 191–208.

[5] Hongqiang Li, Danyang Yuan, Youxi Wang, Dianyin Cui, Lu Cao, Arrhythmia classification based on multi-domain feature extraction for an ECG recognition system, Sensors 2016 (16) (2016) 1744, https://doi.org/10.3390/s16101744.

[6] R. Rodrígueza, A. Mexicanob, J. Bilac, S. Cervantesd, R. Ponceb, Feature extraction of electrocardiogram signals by applying adaptive threshold and principal component analysis, J. Appl. Res. Technol. 13 (2015) (2015) 261–269.

[7] Carlos Lastre-Dom-nguez, Yuriy S. Shmaliy, Oscar Ibarra-Manzano, Jorge Munoz-Minjares, Luis J. Morales-Mendoza, ECG signal denoising and features extraction using unbiased FIR smoothing, BioMed Res. Int. 2019 (2019), 2608547, https://doi.org/10.1155/2019/2608547. Hindawi. 16 pages.

[8] M. Ashtiyani, S. Navaei Lavasani, A. Asgharzadeh Alvar, M.R. Deevband, Heart rate variability classification using support vector machine and genetic algorithm, J. Biomed. Phys. Eng. (2018) 423–434.

[9] M. Zubair, J. Kim, C. Yoon, An automated ECG beat classification system using convolutional neural networks, in: 6th International Conference on IT Convergence and Security (ICITCS), Prague, 2016, pp. 1–5, https://doi.org/10.1109/ICITCS.2016.7740310.

[10] V. Bhagyalakshmi, R.V. Pujeri, Geetha D. Devanagavi, GB-SVNN: genetic BAT assisted support vector neural network for arrhythmia classification using ECG signals, J. King Saud Univ. - Comput. Inf. Sci. (2018).

[11] Jinkwon Kim, Hang Sik Shin, Kwangsoo Shin, Myoungho Lee, Robust algorithm for arrhythmia classification in ECG using extreme learning machine, Biomed. Eng. Online (2009). October.

[12] Alessandro Scirè, Fabrizio Tropeano, Aris Anagnosto poulos, Ioannis Chatzigiannakis, Fog-computing-Based heartbeat detection and arrhythmia classification using machine learning, Algorithms 2019 (12) (2019) 32, https://doi.org/10.3390/a12020032.

[13] Miquel Alfaras, Miguel C. Soriano, Silvia Ortín, A fast machine learning model for ECG-Based heartbeat classification and arrhythmia detection", Front. Phys. 7 (July) (2019), 103.

[14] S. Karimifard, A. Ahmadian, Morphological heart arrhythmia classification using hermitian model of Higher-order statistics, in: 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Lyon, 2007, pp. 3132–3135, https://doi.org/10.1109/IEMBS.2007.4352993.

[15] D. Arotaritei, H. Costin, C. Rotariu, A. Pasarica, Cardiac arrhythmia classification using T-complexity measure, in: International Conference and Exposition on Electrical and Power Engineering (EPE), Iasi, 2016, pp. 431–434, https://doi.org/10.1109/ICEPE.2016.7781377.

[16] E. Izci, M.A. Ozdemir, R. Sadighzadeh, A. Akan, Arrhythmia detection on ECG signals by using empirical Mode decomposition, in: Medical Technologies National Congress (TIPTEKNO), Magusa, 2018, pp. 1–4, https://doi.org/10.1109/TIPTEKNO.2018.8597094.

[17] O. Perlman, Y. Zigel, G. Amit, A. Katz, Cardiac arrhythmia classification in 12-lead ECG using synthetic atrial activity signal, IEEE 27th Convention of Electrical and Electronics Engineers in Israel, Eilat (2012) 1–4, https://doi.org/10.1109/EEEI.2012.6376901.

[18] E. Cimen, G. Ozturk, Arrhythmia classification via k-means based polyhedral conic functions algorithm, in: International Conference on Computational Science and Computational Intelligence (CSCI), Las Vegas, NV, 2016, pp. 798–802, https://doi.org/10.1109/CSCI.2016.0155.

[19] J.M. Lillo-Castellano, et al., Symmetrical compression distance for arrhythmia discrimination in cloud-based big-data services, IEEE J. Biomed. Health Inform. 19 (July (4)) (2015) 1253–1263, https://doi.org/10.1109/JBHI.2015.2412175.

[20] fish 0,punct]">Thripurna Thatipelli, Padmavathi Kora, Electrocardiogram beat classification using Discrete Wavelet Transform, higher order statistics and multivariate analysis, Int. J. Eng. Technol. (IRJET) 04 (July (07)) (2017) 854–858.

[21] A. for the Advancement of Medical Instrumentation, et al., Testing and Reporting Performance Results of Cardiac Rhythm and St Segment Measurement Algorithms, ANSI/AAMI EC38, vol. 1998, 1998.

[22] Shweta H. Jambukia, Vipul K. Dabhi, Harshadkumar B. Prajapati, ECG beat classification using machine learning techniques, Int. J. Biomed. Eng. Technol. 26 (1) (2018) 32–53.

[23] Roshan Joy Martis, U. Rajendra Acharya, K.M. Mandana, A.K. Ray, Chandan Chakraborty, Application of principal component analysis to ECG signals for automated diagnosis of cardiac health, Expert Syst. Appl. 39 (2012) 11792–11800.

[24] Farhana Akter Mou, Muhammed Abdullah Al Mahmud, A.H.M. Zadidul Karim, Salma Nazia Rahman, Shaikh Rashedur Rahman, Classification of electrocardiogram signal using support vector machine based on fractal extraction by FD, Am. J. Circuits Syst. Signal Process. 3 (3) (2017) 12–22.

[25] S.T. Sanamdikar, S.T. Hamde, V.G. Asutkar, Machine vision approach for arrhythmia classification using incremental super vector regression, J. Signal Process. 5 (2) (2019) 1–8, https://doi.org/10.5281/zenodo.2637567.

[26] Rahul Kher, Signal processing techniques for removing noise from ECG signals, J. Biomed. Eng. 1 (2019) 1–9.

[27] Yurong Luo, Rosalyn H. Hargraves, Ashwin Belle, Ou Bai, Xuguang Qi, Kevin R. Ward, Michael Paul Pfaffenberger, Kayvan Najarian, A hierarchical method for removal of baseline drift from biomedical signals: application in ECG analysis, Hindawi Publishing Corporation, Scientific World J. (2013), 896056, https://doi.org/10.1155/2013/896056, 10 pages.

[28] Anurag Trivedi Harimohanrai, Shailja Shukla, ECG signal processing for abnormalities using multi-resolution wavelet transform and artificial neural network classifier, in: Deptt of Electrical Engg, Jabalpur Engineering College, Jabalpur, MP, India, 2020.

[29] Tanya Kambo, Ram Avtarjaswal, De-noising and statistical feature extraction of the ecg signal using wavelet analysis, Int. J. Electr. Electron. Data Commun. 4 (September (9)) (2016).

[30] Mingfeng Jiang, Yaming Wang, Ling Xia, Feng Liu, Shanshan Jiang, Wenqing Huang, The combination of self-organizing feature maps and support vector regression for solving the inverse ECG problem, Comput. Math. Appl. 66 (10) (2013) 1981–1990, https://doi.org/10.1016/j.camwa.2013.09.010. ISSN 0898-1221.

[31] Chun-Cheng Lin, Chun-Min Yang, Heartbeat Classification Using Normalized RR Intervals and Morphological Features, Mathematical Problems in Engineering, 2014, pp. 1–11, https://doi.org/10.1155/2014/712474.

[32] D. Azariadi, V. Tsoutsouras, S. Xydis, D. Soudris, ECG signal analysis and arrhythmia detection on IoT wearable medical devices, in: 2016 5th International Conference on Modern Circuits and Systems Technologies (MOCAST), Thessaloniki, 2016, pp. 1–4, https://doi.org/10.1109/MOCAST.2016.7495143.

[33] P. Singh, A. Jasuja, IoT based low-cost distant patient ECG monitoring system, in: 2017 International Conference on Computing, Communication and Automation (ICCCA), Greater Noida, 2017, pp. 1330–1334, https://doi.org/10.1109/CCAA.2017.8230003.

[34] M.F. Amri, M.I. Rizqyawan, A. Turnip, ECG signal processing using offline-wavelet transform method based on ECG-IoT device, in: 2016 3rd International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE), Semarang, 2016, pp. 1–6, https://doi.org/10.1109/ICITACEE.2016.7892404.

[35] S.T. Sanamdikar, S.T. Hamde, V.G. Asutkar, Cardiac arrhythmia detection on electrocardiogram beats based on KPCA and SVR, Int. J. Emerg. Technol. Learn. 11 (2) (2020) 44–51.

[36] Yakup Kutlu, Damla Kuntalp, Feature extraction for ECG heartbeats using higher order statistics of WPD coefficients, Comput. Methods Programs Biomed. IO5 (2015) 257–267.

[37] Junaid Ahmed Zubairi, Abdul Rahman Alahdal, Muhammad Arshad Malik, IoT-based ambulatory vital signs data transfer system, J. Comput. Netw. Commun. 2018 (2018), 4071474, https://doi.org/10.1155/2018/4071474, 8 pages.

[38] M. Raeiatibanadkooki, S.R. Quachani, M. Khalilzade, K. Bahaadinbeigy, Real time processing and transferring ECG signal by a mobile phone, Acta Inform. Med. 22 (6) (2014) 389–392, https://doi.org/10.5455/aim.2014.22.389-392.

[39] V. Vapnik, Statistical Learning Theory, Wiley, Chichester, GB, 1998.

[40] https://www.physionet.org/content/mitdb/1.0.0/.

[41] G.B. Moody, R.G. Mark, The impact of the MIT-BIH arrhythmia database, IEEE Eng. Med. Biol. 20 (May-June (3)) (2001) 45–50, https://doi.org/10.1109/51.932724 (PMID: 11446209).

[42] S.T. Sanamdikar, S.T. Hamde, V.G. Asutkar, Analysis and classification of cardiac arrhythmia based on general sparsed neural network of, SN Appl. Sci. 2 (7) (2020), 1244, https://doi.org/10.1007/s42452-020-3058-8.