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An Efficient Cardiac Arrhythmia Onset Detection Technique Using a Novel Feature Rank Score Algorithm

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Abstract

The interpretation of various cardiovascular blood flow abnormalities can be identified using Electrocardiogram (ECG). The predominant anomaly due to the blood flow dynamics leads to the occurrence of cardiac arrhythmias in the cardiac system. In this work, estimation of cardiac output (CO) parameter using blood flow rate analysis is carried out, which is a vital parameter to identify the subjects with left- ventricular arrhythmias (LVA). In particular, LVA is a resultant component of characteristic changes in blood rheology (blood flow rate). The CO is an intrinsic parameter derived from the stroke volume (SV) characterized by end-diastolic/systolic volumes (EDV/ESV) and heart rate. The pumping of blood from left ventricle (LV) reconciles in to R-R intervals depicted on ECG, which are used for heart rate estimation. The deviation from the nominal values of CO implies that, the subject is more prone to LVA. Further, the identification of subjects with LVA is accomplished by computing the features from the ECG signals. The proposed Feature Ranking Score (FRS) algorithm employs different statistical parameters to label the score of the extracted features. The feature score enables the selection optimal features for classification. The optimal features are further given to the Least Square- Support Vector Machine (LS-SVM) classifier for training and testing phases. The signals are acquired from public domain MIT-BIH arrhythmia data

base, used for validating the proposed technique for identifying the LVA using blood flow.

Keywords Blood flow · Electrocardiogram (ECG) · Feature ranking score (FRS) · Left ventricular arrhythmia (LVA)

Introduction

The recent study on disease burden and risk reveals the fact that leading individual causes of disability-adjusted life years (DALYs) were ischemic heart diseases and the risk factor for the same was high systolic blood pressure Dandona et al. [11]. Cardiovascular diseases [14] are increasingly growing leading global cause of deaths. The mortality rate in adults is increasingly influenced by the principal and predominant risk factor: the Hypertension. Cardiac Arrhythmias are considered the clinical indexes of patients with hypertension. Left ventricular hypertrophy (LVH) is one of the major complications of hypertensive Sheldon et al. [27] target organ damage and ventricular arrhythmias are a result of the same. The anatomical structure of the heart is in the manner of sequential compartmental blood loading through the different types of arteries and veins. The pre- and after-load of blood throughout the cardiac cycle is depicted by the ventricular chambers. The physiological perseverance of heart is illustrated by its electrical activity that is quantitatively estimated by a non-invasive diagnostic-tool the Electrocardiogram. Electrocardiography test is considered as the renowned non-invasive cardiovascular malfunctioning detection method, because of its easy and simple handling. ECG denotes the collective functioning of the cardiac muscles. The ECG can be fragmented into various segments and intervals whose occurrence can be correlated with the electrical stimulation and mechanical physiology of heart. The physiological and anatomical characteristics

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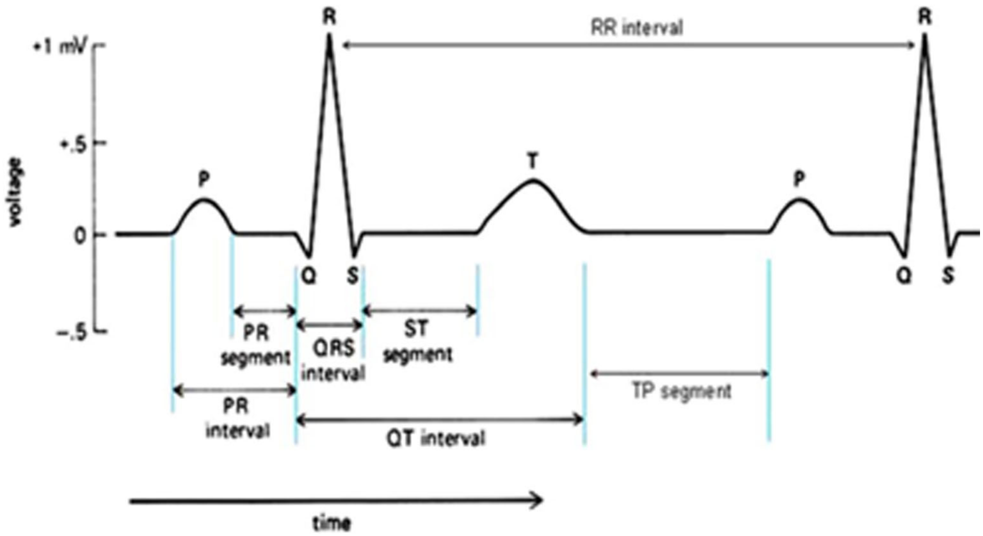

Fig. 1 ECG signal with intervals and segments

of the cardiac system can be predicted with the help of ECG signals acquired from a subject (ECG) (Fig. 1).

The cardiac cycle is composed of following series of events: (a) atrial systole, (b) atrial diastole, (c) ventricular systole and (d) ventricular diastole as shown in Fig. 2. Atrial systole starts the cycle with the help of natural pacemaker, the sino-atrial node. It occurs for 0.1 s, and then occurs the atrial diastole, for 0.7 s. The cycle repeats itself in this pattern for a total duration 0.8 s. The ventricular systole starts with duration of 0.3 s with the end of atrial systole. This is immediately followed by ventricular diastole for duration of 0.5 s. The cycle repeats itself for duration of 0.8 s.

The complex mechanical behavior of heart hemodynamics estimation and validation with experimental values is essential for modeling of cardiac vascular system in terms of feature extraction and steady state modeling Hamde et al. [17]. The pattern of the ECG waveforms is unique and hence any changes in waveform can be used to identify the subject's Cardio vascular functions. The era of Internet of things (IoT) in clinical diagnosis marked its significance with the usage of Support Vector Machine (SVM), which has paved the way for feature extraction, and feature classification thereby promoting the identification of cardiac arrhythmia, premature ventricular contraction and ventricular ectopic beats. SVM classifier is widely used for the classification purposes. The instant of beat is the chain of vector, often called feature vector Roonizi and Sassi [13]. Several features have been proposed to detect concealed dynamical properties of the bio signals. These nonlinear dynamical techniques are applied to the areas of medical sciences and biology. Automated ECG analysis can be enhanced with the genetic algorithm- neural network (GA-NN) [7] which performs simultaneous feature selection and classification Fukuta and Little [16]. Cardiac Arrhythmia detection using ECG signals utilizes Linear Prediction Coefficients

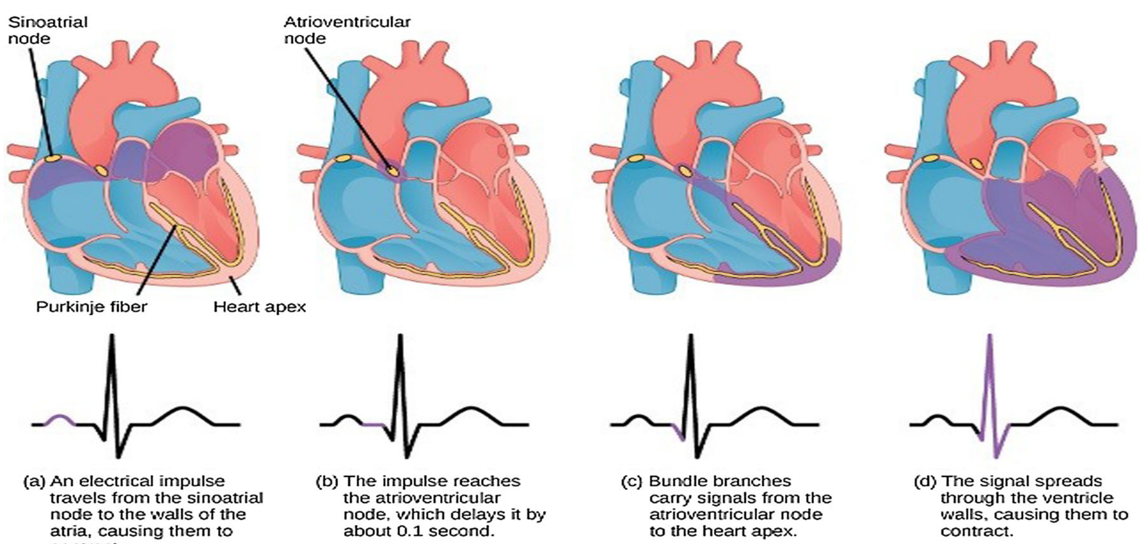

Fig. 2 Interpretation of cardiac cycle in normal ECG waveform

(LPC), which represents the wavelet coefficients Komanduri et al. [23] of the ECG signals taken for diagnosis. The ECG parameter analysis mainly depends on the relevancy of allowing the determination based on the single ranking score. The use of backward selection procedure in SVM classifiers, gives a classifier that is robust by using minimal set of ECG parameters.

Ventricular Arrhythmias are a life-threatening incident, which is significant with the increase or decrease in the heart rate Alonso-Atienza et al. [15]. The condition, which prevails with the increase in heart rate, is called as ventricular tachycardia and decrement in the heart rate is termed as ventricular bradycardia. Both clinical complications are vulnerable to ventricular fibrillation, which finally leads to ventricular arrhythmias. The cardiac malfunctions are contributed by the aberrations in ventricular synchronization with the natural pace. The ventricular fibrillation is initiated by premature ventricular contraction (PVC). This is more significant in the QRS complex of a typical ECG Koplan and Stevenson [8]. The recent trends in the field of soft computing have increased the motivational aspects to aid the clinical sectors. With the advancements in feature extraction algorithms along with ranking score objective functions the task becomes superlative.

The work in this paper handles a method of detecting the various ECG segments and intervals for prompt representation of the heart rate used in the estimation of cardiac output using the ejection fraction. The method also paves the way to extract the features essential for classifying the normal and abnormal status of input ECG signal with respect to ventricular fibrillation [1, 5]. The classification of ventricular arrhythmias is substantiated by specificity and sensitivity of the classifier thereby meting out the objective of the work.

Numerical estimation of cardiac output

Overview of hemodynamics of heart

The ventricles in the heart are responsible for pumping the blood throughout the human body [3]. The ejection fraction (EF) is the percentage of the blood volume ejected from the ventricles [20] during every contraction and relaxation Simioni et al. [10]. EF percent (%) can be determined by using the following equation:

$$EF(\%) = (EDV-ESV)/EDV*100 \tag{1}$$

The Stroke Volume SV is given by,

$$SV = EDV-ESV \tag{2}$$

Cardiac output is the amount of blood pumped by the heart per beat, i.e., heart rate (HR)

$$CO = SV*HR \tag{3}$$

Acquisition of ECG signal

The MATLAB software allows automatic importation of ECG files in. mat format. The MIT-BIH Arrhythmia Database Moodyand Mark [21] contains 48 half-hour ECG recordings, of which 35 samples were chosen at random for experimental purposes. The ECG signals were pre-processed to eliminate noises and baseline wandering. The filtering is done both with low and high pass filters of order 14 and 2 respectively. The entire MIT-BIH Arrhythmia Database contains about 47 complete records, and reference annotation files for all 47 records that are freely available for research purposes.

Classification of ventricular arrhythmia using support vector machine (SVM)

Feature extraction using the proposed algorithm

The feature extraction [2] analysis technique chosen is the decomposition of signal. Decomposition process measures Roonizi and Sassi [13, 12] the similarity between the two input signals and extracts the information present in the signals. Feature extraction ensures minimal use of the data sets. Because of this, a reduction in the computational time is also incorporated. Feature extraction is a general term where different combinations of features [24–26] are used for evaluation.

For improving the classification performance feature selection (FS) Lance and Williams [19] is essential. To detect the arrhythmia signals 13 features or parameters were incorporated. The selected features are placed in three broad categories with usage of 2 s window for a segment of 8 s. The classification of features is as follows:

(i) Temporal Features:

Temporal parameters [22] are placed under spatial domain. They are as follows.

Threshold Crossing Interval (TCI) is based on the signals used and position of signals crossing through a certain threshold value. For this TCI calculation only 1 s segment is preferred.

$$TCI = \frac{1000}{(N-1) + \frac{t_2}{t_1 + t_2} + \frac{t_3}{t_3 + t_4}} \tag{4}$$

where,

N No of pulses in s

t_1 time interval from the start of s and then to the reducing edge of the proceeding pulse

t_2 time interval between next pulse
t_3 time interval of two consecutive end pulse

Threshold crossing Sample Count (TCSC) is applicable for normal rhythm of ECG signal. TCSC occurs after the nominal value of threshold value despite the normal counting pulse.

Standard exponential algorithm (SEA) matches and counts the crossing points of input samples with a decreasing exponential curve

$$E_s(t) = M\exp\left(-\frac{|t-t_m|}{\tau}\right) \tag{5}$$

where,

M amplitude of signal
t_m corresponding time

Modified Exponential (MEA) expanded version of STE called MEA. MEA is the resultant of decreasing exponential curve at the crossing point into relative minimum.

Mean Absolute Value (MAV) is denoted by

$$M\sum_{n=0}^{N-1}|x(n)|AV = \frac{1}{N} \tag{6}$$

where,

N number of samples.

(ii) Spectral Features:

The frequency domain parameters are defined as follows:

VF filter (VF leak) is a narrow band reduction filter in the area of mean frequency of the considered input ECG signal. VF filter leakage is defined as l.

$$1 = \left(\sum_{i=1}^{m}|V_i + V_{i-N}|\right)\left(\sum_{i=1}^{m}\left(|V|_i + |V_{i-N}|\right)\right)^{-1} \tag{7}$$

Spectral moment is given by the following equation

$$M = \frac{1}{\Omega}\frac{\sum_{j-1}^{j_{\max}} a_j\omega_j}{\sum_{j-1}^{j_{\max}} a_j} \tag{8}$$

Where,

Ω frequency of the component with largest amplitude
j_{max} index of the highest investigated frequency and A1, A2, A3
ω_j jth frequency in the FFT between 0 Hz and the minimum of 100 Hz
a_j corresponding amplitude

Median frequency is calculated using

$$FM = \frac{\sum_{i=1}^{n}(f_i - p_i)}{\sum_{i=1}^{n}p_i} \tag{9}$$

where,

Pi is the ith component of frequency fi.

(iii) Complexity Feature:

The complexity parameters give a note of the optimal size of decision system.

Complexity measurement (CM) converts continuous ECG signal into binary sequences and repeating patterns in the same are looked for.

Phase Space Reconstruction (PSR) helps in signal reconstruction and is a model of time delay algorithm. The randomness in the signal is evolved by this parameter.

Hilbert Transform (HILB) xH (t) is especially used for analysis of nonlinear signals.

$$x_H(t) = \frac{1}{n}P\bullet V\int_{-\infty}^{\infty}\frac{x(T)}{t-T}\,dT \tag{10}$$

where,

P.V integral is taken in the sense of the Cauchy principal value.
x_H (t) considered as a convolution of function x (t) and 1/πt.

Sample Entropy (SpEn) enables the restoration of the information in the input ECG signal. SpEn is the result of conditional probability thereby finding the self-matches and omitting them.

Support vector machine for classification

SVM is a machine-learning algorithm, which utilizes sample, based statistical learning algorithm for cross validation. SVM is a binary classifier, which is used to classify the beats. In SVM, there are 4 well known and widely used algorithms [11]. They are one against One (OAO), One against All (OAA), fuzzy decision function and decision direct acyclic graph. These all methods are used to find presence or absence of arrhythmias in the proposed work.

The sequential steps of the proposed algorithm are as follows:

Step 1: Sorting of the features with respect to the grade of filter criterion denoted as s where the first value of the filter criterion $s[1]$ is the highest score variable and n^{th}value $s[n]$ is the lowest graded where n is the number of features of the input space.

Step 2: Initialize the feature matrix 'V' as $V = \{x\langle :, s(.)\rangle, y\}$, where x & y are the corresponding row and column of the feature matrix.

Step 3: Repeat the case for the following condition:

(i) Training of the SVM classifier has to be done using $V = \{x(: , s(1 : j), y\}$, where $j = 1, 2, 3.....d$ and calculate the free parameters such as correlation constant C_j and Fisher's criterion constant γ_j.

(ii) Update $j = j - 1$

Step 4: Repeat the process until $j = 0$

Step 5: Repeat the data set $V = \{x\langle :, s(.)\rangle, y\}, j = d$

Step 6: Bootstrap resample, $V = \{x * \langle :, s(.)\rangle, y*\}, j = d$, are build

Step 7: The steps are continued for the following conditions:

i) Every bootstrap resample r, the corresponding performance of the SVM $P^*(r)$ is computed, $r = 1, 2, ...R$ using the calculated free parameters (C_j, γ_j)

ii) Eliminate the feature with the lowest grade $V = \{x * \langle :, s(.)\rangle, y*\}, j = d\}$, and update $j = j - 1$

Step 8: $j = 0$

The above plot interprets the distribution of the training feature vector set. The TCI and MAV is 1 throughout and contributes less to the testing phase. The analysis of the signals in accordance with the feature selection filtering method holds the essential route to the ranking score for classification.

Results and discussion

Implementation of classification using SVM

The ECG signal with left ventricular arrhythmia based on three-feature vector detection algorithm was calculated. In the Fig. 3, the representation of features is by improving the methods based on our literature survey. The wavelet decomposing methods to analysis variables present in ECG data are also noted down for avoiding redundancy the extracted features of the ECG signal using Correlation Criterion and Fisher Criterion were effectively utilized by SVM in

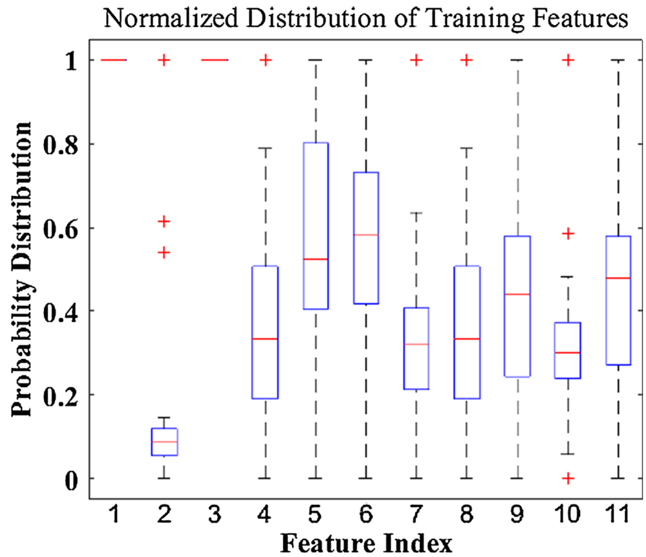

Fig. 3 Plot showing the distribution of training features.

producing the classification accuracy. The above-mentioned criteria select the best fit of features towards the testing set for arrhythmias. In our work out of 47 samples handled from Physio bank were categorized into two groups: those who are prevalent to ventricular arrhythmia (1) and those without (0). The first 35 members were used for training and the next for testing phase.

A. *Feature Selection Criterion Using Fischer criterion*

F-Score Analysis is a simple and effective technique for feature selection Arunasakthi et al. [6, 9] which makes score analysis by distinguishing two sets of real numbers. F-score value for each i^{th} attribute is defined as follows,

$$F(i) = \frac{\left(x_i^{(+)} - x_i\right)^2 + \left(x_i^{(-)} - x_i\right)^2}{{}^1/_{n_+} - 1\left(x_{j,i}^{(+)} - x_i^{(+)}\right)^2 + {}^1/_{n_-} - 1\left(x_{j,i}^{(-)} - x_i^{(-)}\right)} \quad (11)$$

Table 1 Score for feature index using ranking score algorithm

Feature	Correlation score	Fisher score
TCI	1.000	1.00
STE	0.024	0.26
MAV	0.030	0.22
TCSC	0.266	0.08
VF leak	0.412	0.08
SA	0.493	0.07
FM	0.488	0.04
PSR	0.591	0.04
HT	0.732	0.00
CM	0.734	0.00
SE	0.952	0.00

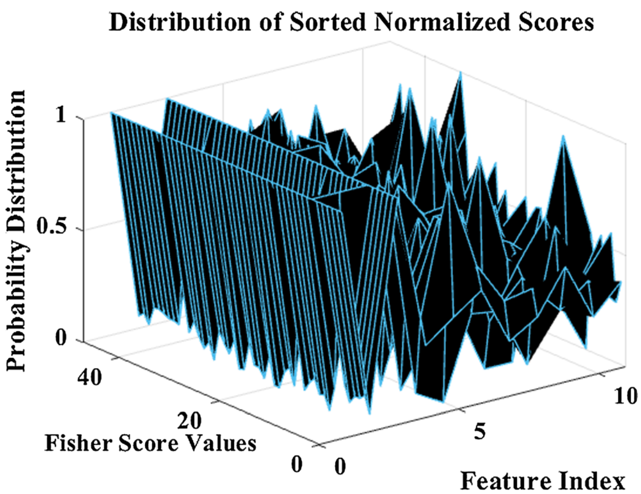

Fig. 4 Distribution of sorted normalized scores

where $\bar{x}_i$ (+), $\bar{x}$ (−) are the average of the ithfeature.

B. *Feature Selection Criterion Using Correlation Criteria*

Correlation criterion [18] finds similarities of each parameter with the evaluated output. For the jth feature x (j) with labels y, the linear correlation coefficient is defined as

$$\rho(j)=\frac{\sum_{i=1}^{N}\left(x_i^{(j)}-\mu_j\right)\left(y_i-\overline{y}\right)}{\sqrt{\sum_i\left(x_i^{(j)}-\mu_j\right)^2\sum_i\left(y_i-\overline{y}\right)^2}} \tag{12}$$

The above table interprets the feature indices with the algorithm proposed. The more prevalent score TCI and SE plays a vital role in identifying the left ventricular arrhythmias. The plot obtained below is the random distribution of features generated through the feature selection algorithm. The below figure shows the contour distribution of the sorted normalized score values where the 4thfeature lies above the threshold 0.6 for estimation of the left ventricular arrhythmias (Table 1).

As per Switching Kalman Filter [4], each heartbeat was compared to the mode in order to build the confusion matrix. In each heartbeats normal mode is denoted as 'n' & 'v' is known as ventricular mode & finally beats are 'X' factor mode consider part of class q. V'V is known as True Positive (TP) V'n is known as False Negative (FP) and N'V is known as False Positive (FP). Beats present on N'q and V'q are harder to classify. Here consider beats Nq as Pseudo False Positive and beats Vq as Pseudo False Negative by using the corresponding Receiver Operating Characteristics (ROC) curve of ECG parameters were analyzed. Here both sensitivity (SE) and specificity (SP) were calculated. Sensitivity is defined as the proportion of VF arrhythmias detection. Specificity is known as the proportion of identification of non-VF arrhythmias.

$$SE=\frac{TP}{(TP+FN)} \tag{13}$$

$$SE=\frac{TN}{(TN+FP)} \tag{14}$$

Here the SVM classifier does the exact classification and the results obtained by the classifier are known as the best result. Here the used 8 features show the most difference between the normal and arrhythmia signal. It is known as the

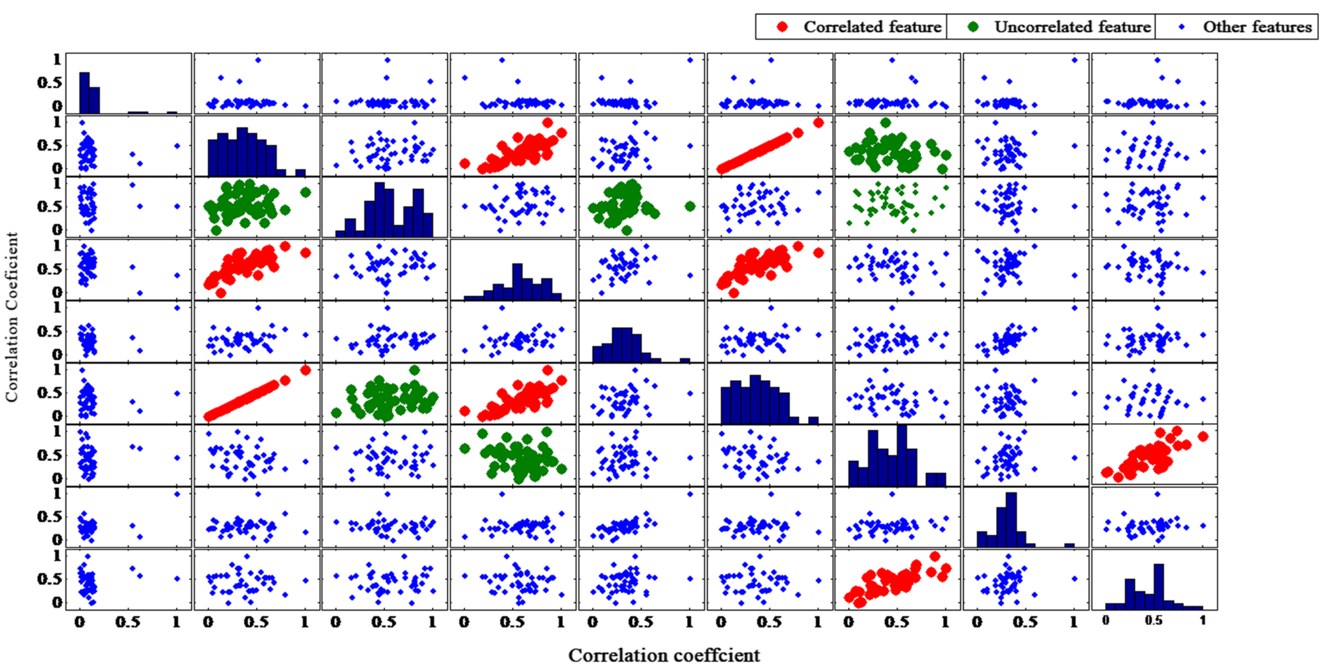

Fig. 5 Correlation score fit of features

Table 2 Ranking of features based on score estimation

Sl no	feature name	Fisher score	Rank	Score combination	Correlation score	Rank
1	TCI	0.00715	5	(1,3)(1,10)	0.1514,0.1522	10
2	STE	0.69111	11	(2,6)(2,8)	0.7122,0.4803	8
3	MAV	0.06499	2	(3,7)	0.9315	2
4	TCSC	0.05491	10	(4,7)(4,8)	0.743,0.7069	3
5	VF_leak	1.65176	8	(5,6)	0.0116	11
6	SA	0.00009	3	(6,2)(6,8)	0.7122,0.5815	7
7	FM	0.00000	4	(7,3),(7,4)(7,8)	0.9315,0.7430,6172	1
8	PSR	0.08192	1	(8,7)	0.6172	6
9	HT	0.00415	9	(9,4)(9,3)	0.5980,0.4969	9
10	CM	0.10436	6	(10,3)(10,11)	0.7517,	5
11	SE	0.90635	7	(11,3),(11,4)	0.6293,0.7230	4

robust method for the ventricular arrhythmias classification. By using the SVM classifier with feature selection and extraction of features results in best classification.

The correlation plot depicts the various categories of features for interpretation of left ventricular arrhythmias: correlated, un-correlated and other features. The correlated features are given by the FSA as {2,3,4,5,6,7,9} whereas the other features don't have major role in the interpretation of LVA. The cardiac output is the initial criterion for the computation of the features by identification of the heart- rate (HR). The literature also substantiates the occurrence of arrhythmias in accordance with the blood flow characteristics back and forth the heart chambers (Figs. 4 and 5).

The proposed algorithm is evaluated on the basis of SVM classsification for arrhythmic signals by ranking the features. The parameters calculated for understanding the efficiency of the classification are sensitivity, specificity and accuracy. For improvising the classification procedure different combinations of the features are taken with respect to their Fisher and Correlation Score. Accordinly the SVM performance estimates are also carried out to precisely define the feature highly influencing the classifiction of the arrhythmic data.

The Table 2 clearly depicts the predominant usage of the features PSR and FM for classification. The step by step elimination of features leads to the efficient classification process. The SVM has yeilded a sensitivity of 96.42%, specificity 94.69% and accuracy of 98.21%.

Conclusion

On a whole, the machine learning system has prodigiously supported the early detection of occurrences of sudden cardiac death due to ventricular fibrillation. The risk factors are to be noted for which the ECG aides in depicting the clinical complication. The advancements in the specificity and accuracy of ECG patterns pave a much easier methodology in approaching the clinical complications in a target-oriented fashion. Our system and algorithm also serves the motive of noticing the calamities at an earlier mode. The future enhancements in the analysis of the ECG signal processing in combination with artificial intelligence will help clinicians to serve patients at a very rapid manner.

Compliance with ethical standards

Conflict of interest This paper has not communicated anywhere till this moment, now only it is communicated to your esteemed journal for the publication with the knowledge of all co-authors.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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