

Automatic Heart Disease Detection by Classification of Ventricular Arrhythmias on ECG Using Machine Learning

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Abstract: This paper focuses on detecting diseased signals and arrhythmias classification into two classes: ventricular tachycardia and premature ventricular contraction. The sole purpose of the signal detection is used to determine if a signal has been collected from a healthy or sick person. The proposed research approach presents a mathematical model for the signal detector based on calculating the instantaneous frequency (IF). Once a signal taken from a patient is detected, then the classifier takes that signal as input and classifies the target disease by predicting the class label. While applying the classifier, templates are designed separately for ventricular tachycardia and premature ventricular contraction. Similarities of a given signal with both the templates are computed in the spectral domain. The empirical analysis reveals precisions for the detector and the applied classifier are 100% and 77.27%, respectively. Moreover, instantaneous frequency analysis provides a benchmark that IF of a normal signal ranges from 0.8 to 1.1 Hz whereas IF range for ventricular tachycardia and premature ventricular contraction is 0.08–0.6 Hz. This indicates a serious loss of high-frequency contents in the spectrum, implying that the heart's overall activity is slowed down. This study may help medical practitioners in detecting the heart disease type based on signal analysis.

Keywords: Heart disease; signals; preprocessing; detection; machine learning

1 Introduction

Machine learning showed significant success in the area of medicine such as heart disease classification [1], brain tumor [2,3], lung cancer [4], skin cancer [5,6], stomach [7,8], Covid19 [9,10], and detection of cancer and hypertension [11,12]. These diseases cause severe consequences; even human deaths like Cardiac Arrhythmia is one of the most common causes of death in the world.



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Cardiac Arrhythmia represents cardiac or heartbeat disorders. It indicates the perturbation in the normal sinus rhythm of the myocardium. In cardiac Arrhythmia, the heartbeat may be very slow, fast, or irregular. It is the unresolved clinical problem causing 0.4 million deaths in the United States annually while in Pakistan, facing cardiac Arrhythmia, and the death rate is almost 15.36% (196,258 people) [13] of total deaths. According to the statistics of the World Health Organization, the death toll caused by cardiovascular disease (CVD) is up to 17.9 million worldwide every year, accounting for 1/3 of the total death toll in the world [14].

This paper focuses on detecting diseased signals and arrhythmias classification into two target classes: ventricular tachycardia and premature ventricular contraction. The main aim is to determine if a signal was collected from a healthy or sick person. The detector works by calculating the instantaneous frequency (IF). First, a given signal is detected from a patient, and a classifier classifies the disease by predicting the class. Applying the supervised learning-based classifier, templates are designed separately for ventricular tachycardia and premature ventricular contraction. Similarities of a given signal with both the templates are computed in the spectral domain.

The heart is the central part of the human body that supplies oxygenated blood to the entire body. It is composed of four valves, and four chambers; [14] the upper chambers are called atria, while the lower chambers are called ventricles. The right ventricle is the lower right part of the heart. When the right atrium contracts, it receives deoxygenated blood. The left ventricle is the lower left part of the myocardium that accepts oxygenated blood from the atrium. The right atrium is the upper right chamber of the heart that receives deoxygenated blood from the body. Left Atrium is the upper left part of the heart. It accepts oxygenated blood from the lungs. Once both atria are filled with blood, they contract, and the oxygenated blood from the left atrium flows into the left ventricle [15]. Veins from the upper body and head go empty into the right atrium of the heart while the veins from the lower parts of the body feed into it, which goes empty into the right atrium of the heart.

1.1 ECG

Electrocardiogram (ECG) represents the amount of electrical activity vs. time. Normally, the ECG signal frequency is 0.05–100 Hz, and the dynamic range is 1–10 mv. ECG signal is recognized by its five peaks denoted by letters of the alphabets P, Q, R, S, and T [16]. Its components explain the ECG, so we present them in a separate heading as below.

1.2 Components of ECG

As shown in Fig. 1, an ECG contains five waves (P, R, Q, S, and T). The P wave is generated with the contraction of the atria [17]. It is the small upward wave that is generated by the first deflection of the heartbeat. It indicates that the atrial vein has an electrical impulse. The magnitude of the P wave is 50–100 mili-volts, and the duration is 100 ms. After the P wave, another wave appears the heartbeat's downward deflection, known as the Q wave. The duration of Q wave is 0.08–0.10 s. The R wave represents the second trough or second peak after the P wave. It intimates the beginning of depolarization in ventricles. The extraction of heart ventricles produces a wave known as T wave. The approximate deflection of T wave is 0.5 mv, and the duration is 0.20 s.

In the normal rhythm, the heart rate ranges from 60 to 100 bpm (beats per minute In electrocardiography. There is no disorder in the signal, then it is called normal sinus rhythm.). When the heart rate increases above 100 bpm, the rhythm is known as sinus tachycardia. If the heart rate

is much slower, it is known as bradycardia [18]. Heart Arrhythmias can be categorized as Sinus Node Arrhythmias, Atrial Arrhythmias, Junctional Arrhythmias, and Ventricular arrhythmias. Disturbance in the Sinoatrial node causes the disturbance in the normal rhythm of the signal; this causes the sinus node arrhythmias [19]. During the sinus node arrhythmias, the P-wave in the ECG is normal. Atrial Arrhythmias arise outside the Sino-atrial node, forming electrical impulses. In this type of Arrhythmia, the heartbeat is very fast that ranges from 160 to 240 bpm, and the QRS complex and a T-wave are normal. The cause of the junctional arrhythmias is the atrioventricular junction node that generates the impulse. These arrhythmias cause the abnormality in P wave. In Ventricular arrhythmias, the impulses arise from the ventricles and go to the rest of the heart outwards. In ventricular arrhythmias, QRS complexes are ample and odd in shape. The ventricular arrhythmias have three types: premature ventricular contractions, ventricular tachycardia, and ventricular fibrillation, as shown in Figs. 2a–2c, respectively.

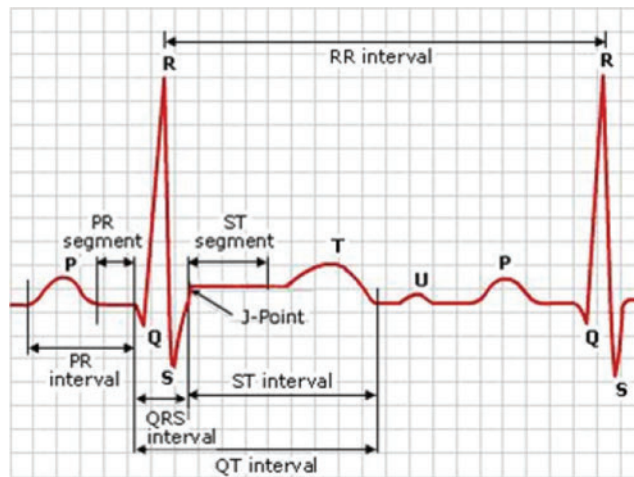


Figure 1: A sample ECG signal and its different components

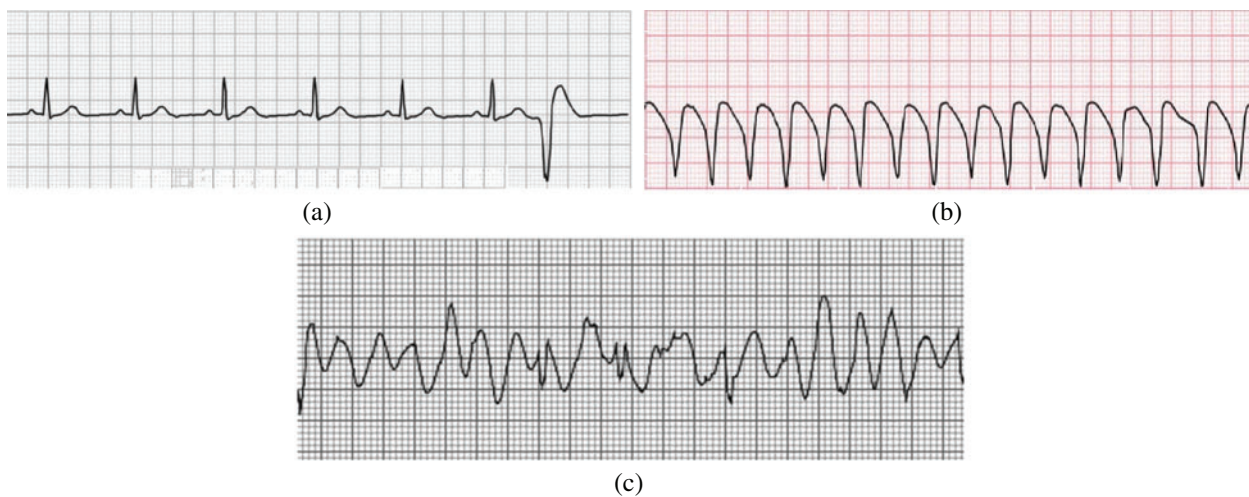


Figure 2: (a) Premature ventricular contraction (b) Ventricular tachycardia (c) Ventricular fibrillation

This work aims at detecting automatic heart disease by classification of ventricular arrhythmias on ECG using machine learning techniques.

- i. The proposed methodology helps determine and detect whether the person belongs to a healthy or a diseased category.
- ii. This proposed research methodology consists of preprocessing, resampling and normalization, and the detector is also designed.
- iii. Mathematical modeling is presented for signal detection, template, detector.
- iv. The proposed system shows enhanced performance results as compared to existing approaches I the relevant literature.

The paper's remainder is arranged as follows: Section 2 discusses the literature work related to the problem and discusses methods related to the classification of ventricular arrhythmias from ECG; in Section 3, the research methodology followed in this paper is given. Section 4 presents and discusses the results of the findings, and in Section 5 conclusion of the overall research work is given.

2 Related Work

Digital signal and data processing is a significant research domain in biomedical engineering research. Researchers from different parts of the world have applied different method and techniques for the automatic detection of heart diseases. Various methodologies have been implemented for digital signal preprocessing, feature extraction from ECG and ECG signals, specifically ventricular arrhythmias signals classification.

2.1 Artifacts in ECG Signals and Feature Extraction

The ECG signals are normally corrupted with different types of noise. Signal preprocessing extracts the required information from a noisy ECG signal. There are various types of artifacts that can cause abnormal ECG patterns; signals become noisy and distorted. Base-line drift can be caused in ECG signals when breathing [20]. Its frequency is 0.25 Hz. To remove baseline drift, a notch filter is used [19]. Additive white Gaussian noise is assumed as noise statistics. To remove noise, we use a low pass filter with a cut-off frequency of 0.2 Hz [21].

The features of ECG signals include the information regarding classification present in the signals. To recognize and extract different ECG waveforms features, a neuro-fuzzy approach has been used [22]. It applied two techniques to characterize the QRS complex by using Hermite polynomials and Hermite kernel expansion coefficients. The research consisted of Markov modeling techniques to detect and analyze QRS complex and R-R intervals as ECG features to classify ventricular Arrhythmia, which researchers used [23]. This technique was used to detect low amplitude P wave from the ECG signal. A wavelet transform based approach extracts P, T and QRS waves and baseline artefacts. Frequency domain, time domain and statistical feature were utilized in [24] for feature extraction. According to this approach, for each segment that is extracted from the signal, the attributes P, Q, R, S and T are determined by discrete wavelet to transform [25,26].

An efficient approach to retrieve features from ECG signals is given in [27]. A synthesis coding technique was presented. The algorithm used in that approach has predefined distortion to encode each heartbeat to extract ECG features while maintaining the defined distortion level [28]. Zhao et al. used wavelet transform and support vector machine for ECG feature extraction and heart rhythms classification [29]. A multiresolution wavelet transform was introduced in 2005 to extract

feature from the ECG signals. It used the modified lead II for signal processing. The researchers used records from the MIT-BIH Database to apply two different types of wavelet filters which are Daubechies4 and Daubechies6.

2.2 Ventricular Diseases Classification Approaches

In ECG classification analysis, most of the researchers have focused on increasing the accuracy level of classification. Several computational approaches have been applied, such as neural networks, digital signal analysis, statistical techniques and support vector machine. Detection of life-threatening ventricular arrhythmias in real-time was addressed by [30,31]. An algorithm named DIAGNOSIS was developed to classify ECG signals using four parameters regarding frequency domain. Sets of rules were used that were based on the comparison of the parameters with predefined thresholds. Four types of signals were discriminated including ventricular fibrillation, imitative artifacts, ventricular rhythms and predominant sinus rhythm. The sequential hypothesis method was detected between two ventricular Arrhythmia; ventricular fibrillation and ventricular tachycardia [32]. The researchers in [33] used early detection automatic detection based on artificial intelligence to assist the ophthalmologist in testing the eyes to avoid blindness and provide a more precise and reliable assessment of a patient's condition. Diabetic retinopathy (DR) is an inevitable retinal disease caused by diabetes. The patient's elevated blood sugar level causes DR, which is difficult to treat. Since no early signs occur at the initial level, they can't be identified early. A generalized discriminant analysis (GDA) technique and a multi-layer perceptron (MLP) neural network classifier were utilized by [34] to develop an effective algorithm for arrhythmia classification. Nine features were obtained from the heart rate variability (HRV) signals.

The novel multi-threaded fitness evaluation approach and the genetic algorithm were used to handle many data sets. A backpropagation neural network addressed by [35] used discrete wavelet transform to classify ECG signals. The features were broken up into two classes: discrete wavelet transform-based features and morphological features. The feed-forward backpropagation and logistic regression variable selection method was used for classification [36,37].

There are several shortcomings in the above-discussed techniques. Some approaches consider a long period for processing, while others are dependent on the ECG signal characteristics. Some of the classifiers need an artifact removal procedure. A few algorithms analyze one part of the signal and detect only one or two abnormalities. It is observed that a common problem with the above-discussed techniques is that when the size of the training parameters increases, structural complexity also grows.

3 Research Methodology

This paper's research methodology consists of preprocessing, resampling and normalization; and is discussed in detail in later sections. In this paper, the model of the signals is considered as:

$$x(n) = s(n) + \eta(n) \quad (1)$$

where $s(n)$ and $\eta(n)$ are true ECG signal and additive white Gaussian noise. The spectrum $\hat{\eta}(n)$ of $\eta(n)$ is:

$$\hat{\eta}(n) = N_0 \quad (2)$$

where N_0 is a constant

3.1 Preprocessing

We carry out the following steps in preprocessing to achieve the same sampling rate with the same signal powers. ECG signals we obtained are sampled at different sampling rates. Also, signals are recorded using different machines, which may cause some comparative amplification/attenuation to signals.

Resampling This step resamples the signals so that all signals have the same sampling rate.

Normalization Signals are normalized so that the power of every signal is unity. Let $x_i(n)$ and $\hat{x}_i(n)$ be a signal and its normalized form, for $1 \leq n \leq N$.

$$\hat{x}_i(n) = \frac{x_i(n)}{d} \quad (3)$$

where d is defined as follows.

$$d = \sqrt{\sum_{n=1}^N x_i(n)^2} \quad (4)$$

3.2 Design of Detector

For a time-frequency distribution $P(\omega; t)$, the frequencies' expected value at a particular time is defined by Eq. (5). As IF has no single definition, one good possibility is to define IF as an expectation of all the frequencies of all the tones in the signal. We find IF for respiration. As the signals are discrete, the process is as follows.

For a signal $x(n)$ of length N , spectrum $\hat{x}(k)$ of $x(n)$ is computed as:

$$\hat{x}(k) = \left| \frac{1}{N} \sum_{n=1}^N x(n) \cdot \exp\left(-\frac{2\pi j(k-1)(n-1)}{N}\right) \right| \quad (5)$$

$$f(k) = \pi(k-1)/(N-1) \quad (6)$$

For $1 \leq k \leq N$, and \hat{x} and f are vectors of the spectral density and corresponding frequency values. Instantaneous frequency (IF), $\langle \omega \rangle$, is calculated as given below.

$$\langle \omega \rangle = \sum_{k=1}^N f(k) \hat{x}(k) \quad (7)$$

3.3 Design of Template

Let $S = \{x_i[n]\}_{1 \leq i \leq M}$ be a set of ECG signals, of a disease, for training, where i is an integer and $i \in [1, M]$. We shortly write x_i in place of $x_i[n]$ and $x_i \in R^N$. Let us consider a template vector $f \in R^N$ as a linear combination of all x_i as follows.

$$f = k_1 x_1 + k_2 x_2 + k_3 x_3 + \dots + k_M x_M \quad (8)$$

where $k_j \in R$ and $x_j \in S$. The coefficients k_j are computed as:

$$k_j = \langle x_j, f \rangle \quad (9)$$

where $\langle x_j, f \rangle$ is a dot product of x_j and f . Consider a matrix $X \in \mathbb{R}^{N \times M}$ as follows.

$$X = (x_1 \ x_2 \ x_3 \ \dots \ x_M) \quad (10)$$

where x_i (for $1 \leq i \leq M$) are vectors and are columns of X . Eq. (8) is rewritten in matrix form, as follows.

$$f = XK \quad (11)$$

$$K = \begin{pmatrix} k_1 \\ k_2 \\ k_3 \\ \vdots \\ k_M \end{pmatrix} \quad (12)$$

$$C = \begin{pmatrix} c_1 \\ c_2 \\ c_3 \\ \vdots \\ c_M \end{pmatrix} \quad (13)$$

where $c_i \in \mathbb{R}$ for $i \in [1, M]$. The matrix C is computed as:

$$C = X^T f \quad (14)$$

$$C = X^T XK \quad (15)$$

$$K = (X^T X)^{-1} \quad (16)$$

3.3.1 Complexity Analysis of the Template Design

Complexity of the equation $K = (X^T X)^{-1} C$ is computed as follows. The equation involves multiplication of two matrices of sizes $M \times N$ and $N \times M$. Therefore, the complexity of multiplication is $O(M^2 N)$. Then an inverse of a matrix of size $M \times M$ requires a complexity of $O(M^3)$. Therefore, the overall complexity for computation of Eq. (16) is $O(M^2 N) + O(M^3)$. As $N > M$, complexity turns out to be $O(M^2 N)$. Eq. (11) involves multiplication of a matrix of size $N \times M$ with a vector of size $M \times 1$. Therefore, the complexity of this multiplication is $O(MN)$. Therefore, the overall complexity is $O(M^2 N) + O(MN) = O(M^2 N)$.

3.4 Classifier

It is assumed that the templates are different from each other for different diseases. Suppose the classifier is designed to calculate a signal's similarity with both the templates and decide (label). This task is performed in the spectral domain. Eq. (5), with a change of units, is rewritten as:

$$\hat{x}(k) = 10 \log_{10} \left| \frac{1}{N} \sum_{n=1}^N x(n) \cdot \exp \left(-\frac{2\pi j(k-1)(n-1)}{N} \right) \right| \quad \text{for } 1 \leq k \leq N \quad (17)$$

The sequence of spectral coefficients $\hat{x}(k)$ given by the above equation is called power spectral density in decibels, where f is the same as given by Eq. (6). Let $\hat{x}(k)$, $\hat{f}_1(k)$ and $\hat{f}_2(k)$ be power spectral densities of a given signal and both the templates, respectively, having means m_x , m_{f1} and m_{f2} . The similarity metric $S(\hat{x}, \hat{f}_1)$ between $\hat{x}(k)$ and $\hat{f}_1(k)$ is computed as follows.

$$S(\hat{x}, \hat{f}_1) = \sum_{k=1}^N (\hat{x}(k) - m_x) (\hat{f}_1(k) - m_{f1}) \quad (18)$$

$$S(\hat{x}, \hat{f}_2) = \sum_{k=1}^N (\hat{x}(k) - m_x) (\hat{f}_2(k) - m_{f2}) \quad (19)$$

$$S(\hat{x}, \hat{f}_1) \underset{C_2}{\overset{C_1}{\geq}} S(\hat{x}, \hat{f}_2) \quad (20)$$

3.5 Detection Algorithm

The algorithm for detecting a patient's condition and detecting whether a person belongs to a healthy or diseased category is given below.

Training Phase of Detector Design of the detector for training is given below.

Input: $X_1 \in R^{N \times M_1}$, $X_2 \in R^{N \times M_2}$ where the column of the matrix X_1 and X_2 are healthy ECGs and diseased ECGs with PVC or VT characteristics, respectively. The numbers of ECG healthy signals and PVC or VT characteristics are M_1 and M_2 , respectively.

Output: A threshold λ .

Algorithm:

1. $X_1 \leftarrow$ Normalize X_1 (normalize every column using Eq. (3)).
2. Compute ω_i^1 ($1 \leq i \leq M_1$) instantaneous frequencies for every column of X_1 using Eq. (7).
3. $X_2 \leftarrow$ Normalize X_2 (normalize every column using Eq. (3)).
4. Compute ω_j^2 ($1 \leq j \leq M_2$) instantaneous frequencies for every column of X_2 using Eq. (3).
5. Set λ to optimize any one of the following relations, for all I, j

$$\omega_i^1 < \lambda < \omega_j^2 \quad (21)$$

$$\omega_i^1 < \lambda < \omega_j^2 \quad (22)$$

Test Phase of Detector Test phase algorithm of the detector is given below.

Input: An arbitrary ECG signal, $x(n)$, in vector form, and λ a threshold (found in Step 5 of the training phase of the detector).

Output: Decision whether $x(n)$ belongs to a healthy or diseased person.

1. $x(n) \leftarrow$ Normalize $x(n)$ (normalize using Eq. (3)).
 2. Compute ω for $x(n)$ using Eq. (7).
 3. Compare ω with λ and decide whether $x(n)$ belongs to a healthy or diseased person.
-

3.6 Classification Algorithms

There are two parts of classification. One is training the process, which is given in the form of an algorithm given as a Training Algorithm. In the second part, signals were introduced to the classifying algorithm given as Testing Algorithm to know whether the signal has ventricular tachycardia or premature ventricular contraction. **The training Algorithm** is given below.

Input: Matrices $X_1 \in R^{N \times M_1}$, $X_2 \in R^{N \times M_2}$ and T (sampling rate). Every column of matrix X_1 is a single ECG with PVC characteristics. Every column of matrix X_2 is a single ECG with VT characteristics. Dimensions M_1 and M_2 are numbers of ECG signals having PVC and VT characteristics, respectively.

Output: Power spectral densities \hat{f}_1 and \hat{f}_2 of templates of C_1 and C_2 , respectively.

1. $X_1 \leftarrow$ Resample X_1 at T
2. $X_1 \leftarrow$ Normalize X_1 (normalize every column using Eq. (3))
3. Set $C_1 \in R^{M_1}$ with arbitrary values
4. Compute $K_1 = (X_1^T X_1)^{-1} C_1$
5. Find template f_1 , in time domain, for PVC by $f_1 = X_1 K_1$
6. Compute power spectral density \hat{f}_1 of f_1 using Eq. (21).
7. $X_2 \leftarrow$ Resample X_2 (resample every column at a rate T)
8. $X_2 \leftarrow$ Normalize X_2 (normalize every column using Eq. (3))
9. Set $C_2 \in R^{M_2}$ With arbitrary values.
10. Compute $K_2 = (X_2^T X_2)^{-1} C_2$
11. Find template f_2 , in time domain, for VT by $f_2 = X_2 K_2$.
12. Compute power spectral density \hat{f}_2 of f_2 using Eq. (21).

The testing Algorithm is given below.

Input: An ECG signal, $x(n)$, with PVC or VT, in vector form; and \hat{f}_1 and \hat{f}_2 ; and sampling rate T .

Output: Decision whether $x(n)$ belongs to C_1 or C_2 .

1. $x(n) \leftarrow$ Resample $x(n)$ (at a rate T if not already sampled at T).
 2. $x(n) \leftarrow$ Normalize $x(n)$ (normalize using Eq. (3)).
 3. Calculate power spectral density, $\hat{x}(n)$ of $x(n)$ using Eq. (21).
 4. Compute $S(\hat{f}_1, \hat{x})$ and $S(\hat{f}_2, \hat{x})$.
 5. Decide VT if $S(\hat{f}_1, \hat{x}) > S(\hat{f}_2, \hat{x})$, else decide PVC.
-

3.7 Complexity Analysis of Algorithms

Complexities of steps of Training Algorithms and Classification Algorithms are given in Tabs. 1 and 2 respectively.

4 Results and Discussions

We have used three datasets, namely MIT-BIH Normal Sinus Rhythm (nsrdb) [38], MIT-BIH Arrhythmia Database (mitdb) [38] and MIT-BIH MalignantVentricular Ectopy Database (vfdb) [38], for detection and classification purpose. Every ECG is in vector form. Such a form of data represents the input to experiments. We carried out simulations using Matlab software.

Table 1: Complexity analysis of training algorithm

Step No.	Computational complexity
1	$O(N \log_2 N)$
2	$O(MN)$
3	$O(M)$
4	$O(M^2 N)$
5	$O(MN)$
6	$O(N \log_2 N)$
7	$O(N \log_2 N)$
8	$O(MN)$
9	$O(M)$
10	$O(M^2 N)$
11	$O(MN)$
12	$O(N \log_2 N)$
Overall complexity	$O(NM^2)$

Table 2: Complexity analysis of testing algorithm

Step No.	1	2	3	4	5	Complexity
Complexity	$O(N \log_2 N)$	$O(MN)$	$O(N \log_2 N)$	$O(N)$	$O(1)$	$O(NM)$

4.1 Preprocessing

Data preprocessing included two steps: namely normalization and resampling. Normalization is performed for all the signals in the processes of detection and classification. [Tab. 3](#) shows the datasets and respective sampling rates. [Tab. 4](#) shows the datasets for Training and Testing Algorithms. For detection, signals are not resampled as it is possible to compute instantaneous frequencies for any arbitrary sampling rate. For the classification of diseases, ECGs taken from MITBIH Arrhythmia Database are resampled at 0.004 sec as shown in [Tabs. 5](#) and [6](#).

Table 3: Datasets and number of ECGs considered for the research

Dataset	No. of ECGs	Signals
MIT-BIH normal Sinus rhythm	12	16265, 16272, 18177, 17453, 17052, 16795, 16786, 16273, 16420, 16483, 16539, 16773
MIT-BIH Arrhythmia database	32	102, 104, 105, 106, 107, 108, 109, 114, 116, 118, 119, 123, 124, 200, 201, 202, 203, 205, 207, 208, 210, 213, 214, 215, 217, 219, 221, 223, 228, 233, 234
MIT-BIH malignant ventricular database	15	420, 421, 423, 425, 427, 428, 430, 602, 605, 607, 609, 611, 612, 614, 615

Table 4: Datasets for training and testing algorithms

Type	Normal	PV	VF
Training	6	16	8
Testing	6	15	17

Table 5: Datasets and corresponding sampling rate

Dataset	Sampling rate (s)
MIT-BIH normal Sinus rhythm	0.0078125
MIT-BIH Arrhythmia database	0.0027777
MIT-BIH malignant ventricular ectopy database	0.004

Table 6: Datasets and IF-values while training the detector

Dataset	IF-values
Normal Sinus rhythm	0.8352, 0.9613, 0.7039, 0.9699, 1.0054, 0.9803
Arrhythmia database	0.3908, 0.4153, 0.3428, 0.549, 0.3453, 0.2135, 0.2548, 0.5531, 0.2686, 0.1596, 0.2447, 0.1932, 0.1972, 0.4509, 0.4053, 0.481
Malignant vent. ectopy	0.2852, 0.5409, 0.4702, 0.3805, 0.0978, 0.081, 0.2826, 0.427

4.2 Results of Detection and Classification

4.2.1 Training

As given in [Tab. 7](#), 30 records were given as input to the detector's training part. [Tab. 7](#) shows the instantaneous frequencies of all the 30 signals. From [Tab. 7](#), we set the value of IF as 0.7. Therefore, any value of IF smaller than 0.7 indicates that the given signal is diseased.

Table 7: Signals used in training and testing

Phase	Signals used
Training	16265, 16272, 18177, 17453, 17052, 16795, 102, 104, 105, 106, 107, 108, 109, 114, 116, 118, 119, 123, 124, 200, 201, 202, 420, 421, 423, 425, 427, 428, 430, 602
Testing	16786, 16273, 16420, 16483, 16539, 16773, 203, 205, 207, 208, 210, 213, 214, 215, 217, 219, 221, 223, 228, 233, 234, 602, 605, 607, 609, 611, 612, 614, 615

Detection rate during training is 100%. Next, the diseased signals were introduced to the classifier's training part to achieve the templates' power spectral densities. K_1 and K_2 set for training are shown in [Figs. 3a](#) and [4b](#). And [Tab. 8](#) shows the values of K_1 and K_2 , plotted in [Figs. 3a](#) and [3b](#).

[Figs. 4, 5](#) shows the templates and their power spectral densities, respectively. It is observed that there is a wide difference between the power spectral densities of the two templates.

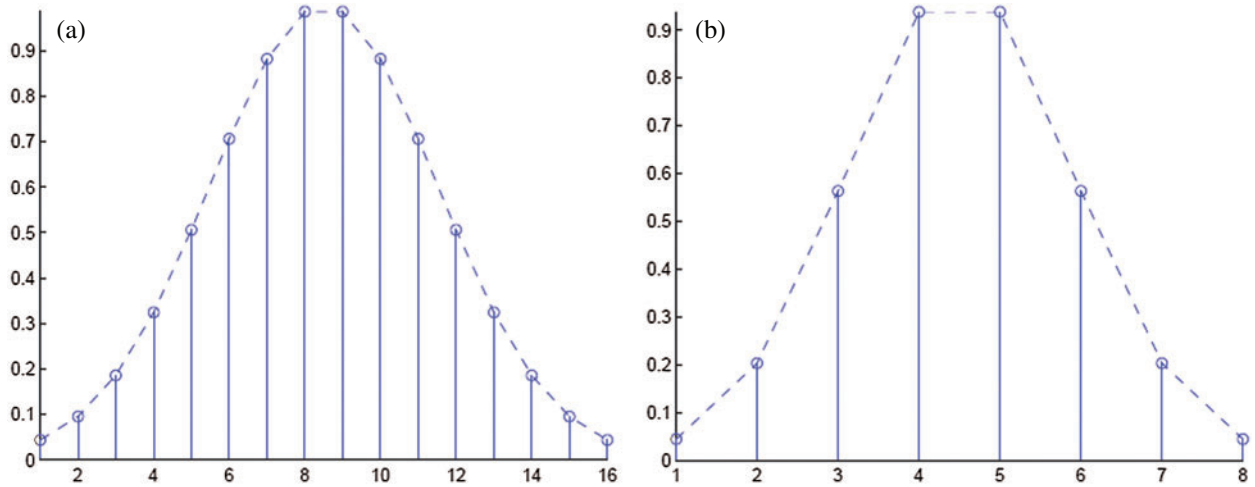


Figure 3: (a) Coefficients C_1 set for the template for signals taken from MIT-BIH Arrhythmia database (b) Coefficients C_2 set for the template for signals taken from MIT-BIH malignant ventricular ectopy database

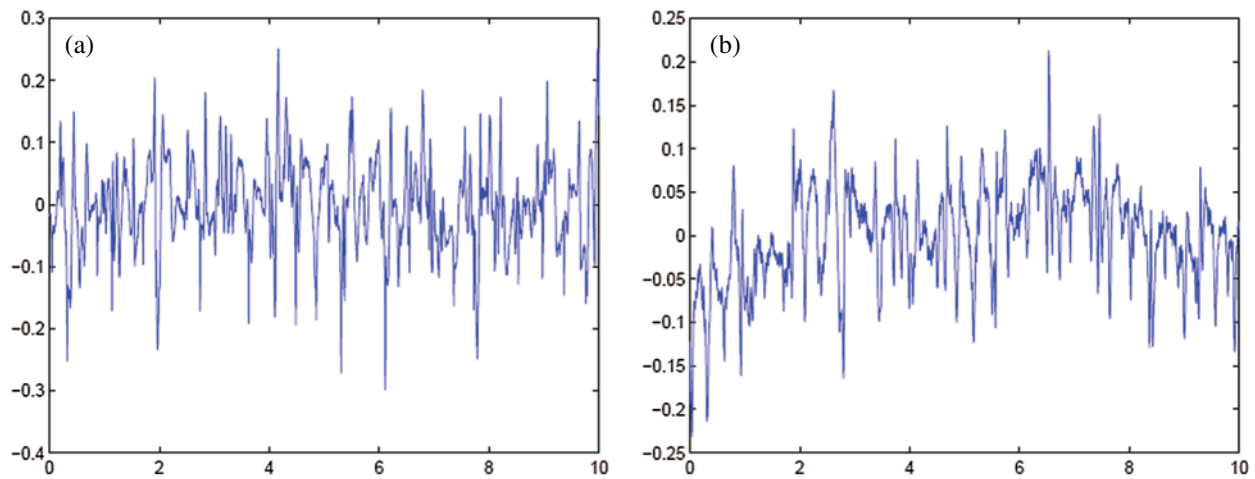


Figure 4: (a) Template for signals taken from MIT-BIH Arrhythmia database (b) Template for signals taken from MIT-BIH malignant ventricular ectopy database

Table 8: Values of K_1 and K_2

K_1	0.0439	0.0956	0.1863	0.3247	0.5063	0.7066	0.8825	0.9862	0.8825	0.7066	0.5063
K_2	0.0439	0.203	0.5633	0.9382	0.9382	0.5633	0.203				

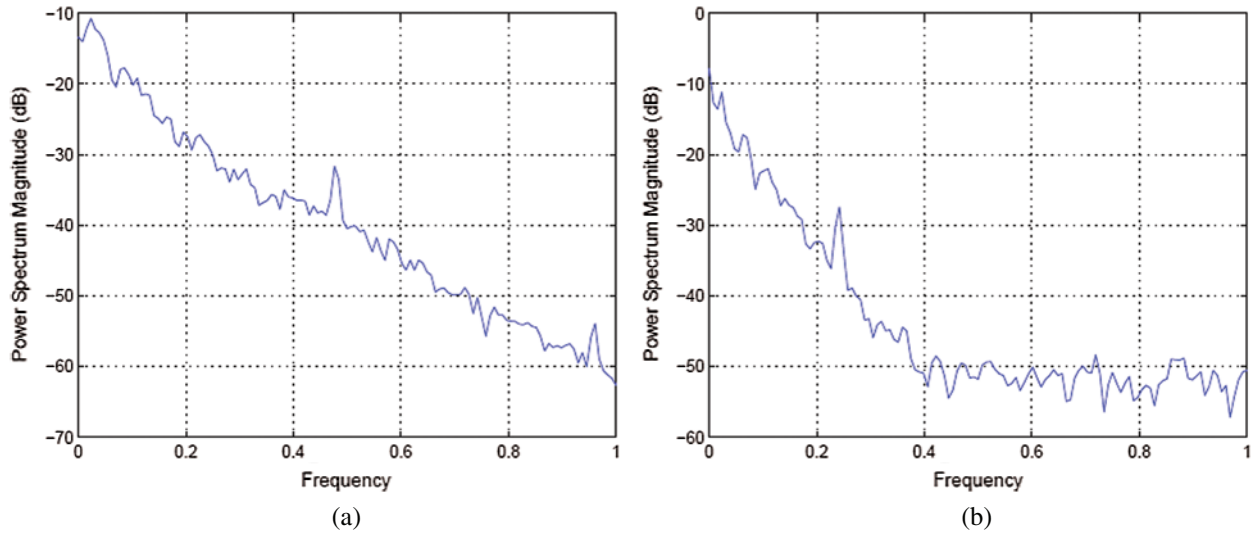


Figure 5: (a) Power spectral density of template for signals taken from MIT-BI Arrhythmia database (b) Power spectral density of template for signals taken from MIT-BIH malignant ventricular ectopy database

4.2.2 Testing

As given in [Tab. 7](#), 26 records were given as input to the detector's testing part. [Tab. 7](#) shows the instantaneous frequencies of all 28 signals. All the diseased signals are below 0.7, and normal signals are above 0.7. Therefore, 22 signals of the two diseases were subject to the classifier. Results of the classifier for both the diseases are given in [Tabs. 9](#) and [10](#).

Table 9: Datasets and IF-values after testing of detector

Dataset	IF-values
Normal Sinus rhythm	0.9188, 0.8874, 1.0804, 0.887, 1.0315, 0.8938
Arrhythmia database	0.5695, 0.2462, 0.2988, 0.4252, 0.4422, 0.3835, 0.4225, 0.5007, 0.3919, 0.3142, 0.4732, 0.2735, 0.296, 0.3935, 0.4939
Malignant vent. ectopy	0.5114, 0.374, 0.404, 0.5045, 0.3158, 0.458, 0.5196

4.3 Performance Analysis

In order to test the effectiveness of the proposed detector and classifier, standard performance metrics have been used, such as sensitivity, specificity, and precision.

Considering [Tab. 7](#), with the value of λ as 0.7, we have 6 normal ($N_P = 6$) and 22 diseased signals ($N_N = 22$) as a test dataset to the detector; thus $N = 28$. All 6 healthy signals were classified correctly. Therefore, $T_P = 6$ and $F_P = 0$. It is observed that $T_N = 22$ and $F_N = 0$. Ideally, the values of all these measurements must be 1. We found 100% performance analysis results of detector whereas; performance analysis of the classifier in the classification of arrhythmias is 77.27 percent.

Table 10: $S(\hat{f}_1, \hat{x})$ and $S(\hat{f}_2, \hat{x})$ with classification decisions and real labels. Signals are in order

$S(\hat{f}_1, \hat{x})$	$S(\hat{f}_2, \hat{x})$	Decision	Real label
0.663760264	0.916298454	PVC	PVC
0.282300751	0.99466931	PVC	PVC
0.379595135	0.996645516	PVC	PVC
0.813273941	0.50230313	VT	PVC
0.632965133	0.938918205	PVC	PVC
0.476326468	0.975082568	PVC	PVC
0.903269023	0.446639397	VT	PVC
0.486279888	0.973163926	PVC	PVC
0.853824353	0.446130412	VT	VT
0.346451853	0.999616871	PVC	PVC
0.759368053	0.843316651	PVC	PVC
0.338819816	0.998915766	PVC	PVC
0.314611294	0.998405087	PVC	PVC
0.508293142	0.980992851	PVC	PVC
0.750130734	0.830672137	PVC	PVC
0.3554757	0.993536324	PVC	VT
0.743128129	0.591626894	VT	VT
0.710279424	0.433968715	VT	VT
0.855829155	0.090706231	VT	VT
0.291176134	0.996170479	PVC	VT
0.806895893	0.580148512	VT	VT
0.943785289	0.46570739	VT	VT

Considering [Tab. 7](#), we have taken 15 signals from MIT-BIH Arrhythmia Database with a label PVC ($NP = 15$) and 7 signals from MIT-BIH Malignant Ventricular Ectopy Database ($NN = 7$) with a label of VF, as a test dataset subjected to the classifier, thus $N = 22$. Again from [Tab. 4](#), it is clear that $TP = 12$, $FP = 3$, $TN = 5$ and $FN = 2$. Ideally, the values of all these measurements must be high. Performance analysis of the classifier is given in [Tab. 11](#).

Table 11: Performance analysis of the classifier, in classification of arrhythmias

Metric	S_n	S_p	PPV	NPV	P
Measure (%)	85.71	62.5	80	71.43	77.27

5 Conclusion

In this research, we designed algorithms for the detection and classification of ventricular cardiac diseases. Firstly, the detection algorithm works for the detection of a diseased signal. Normal signals were taken from MIT-BIH Normal Sinus Rhythm. If a given signal is diseased, it passes through the classifier to identify the disease. We considered only two diseases: ventricular tachycardia (taken from MIT-BIH Malignant Ventricular Ectopy Database) and premature ventricular contraction (taken from MIT-BIH Arrhythmia Database). Signals taken from every

database were divided into two sets. One set was introduced in the training of the detector and classifier. The other set was used to test and observe the performance of the proposed detector and classifier. Through the evaluation process, the main conclusion drawn is as follows. Removal of noise and wander baseline are not necessary if the signals are transformed to a spectral domain. As it is assumed that signals have additive white Gaussian noise, there is a constant value added to the signals' spectrum. This does not affect the value of the instantaneous frequencies and does not affect decisions drawn from spectra of the templates. As far as wander baseline is concerned, its magnitude is so small that it has a little effect on IF spectra of templates. It has been observed that the same results are obtained if X_1 is resampled to the sampling rate of X_2 and vice versa. High values of instantaneous frequencies for normal signals show that high-frequency components are suppressed in the case of diseased signals.

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References

- [1] J. P. Li, A. U. Haq, S. U. Din, J. Khan and A. Saboor, "Heart disease identification method using machine learning classification in e-healthcare," *IEEE Access*, vol. 8, pp. 107562–107582, 2020.
- [2] M. I. Sharif, M. Alhussein, K. Aurangzeb and M. Raza, "A decision support system for multimodal brain tumor classification using deep learning," *Complex & Intelligent Systems*, vol. 11, pp. 1–14, 2021.
- [3] I. Ashraf, M. Alhaisoni, R. Damaševičius, R. Scherer, A. Rehman *et al.*, "Multimodal brain tumor classification using deep learning and robust feature selection: A machine learning application for radiologists," *Diagnostics*, vol. 10, pp. 565, 2020.
- [4] M. A. Khan, S. Rubab, A. Kashif, M. I. Sharif, N. Muhammad *et al.*, "Lungs cancer classification from CT images: An integrated design of contrast based classical features fusion and selection," *Pattern Recognition Letters*, vol. 129, pp. 77–85, 2020.
- [5] Y.-D. Zhang, M. Sharif and T. Akram, "Pixels to classes: Intelligent learning framework for multiclass skin lesion localization and classification," *Computers & Electrical Engineering*, vol. 90, pp. 106956, 2021.
- [6] T. Akram, Y.-D. Zhang and M. Sharif, "Attributes based skin lesion detection and recognition: A mask RCNN and transfer learning-based deep learning framework," *Pattern Recognition Letters*, vol. 3, pp. 1–7, 2021.
- [7] M. S. Sarfraz, M. Alhaisoni, A. A. Albeshir, S. Wang and I. Ashraf, "StomachNet: Optimal deep learning features fusion for stomach abnormalities classification," *IEEE Access*, vol. 8, pp. 197969–197981, 2020.
- [8] S. Kadry, M. Alhaisoni, Y. Nam, Y. Zhang, V. Rajinikanth *et al.*, "Computer-aided gastrointestinal diseases analysis from wireless capsule endoscopy: A framework of best features selection," *IEEE Access*, vol. 8, pp. 132850–132859, 2020.
- [9] T. Akram, S. Gul, A. Shahzad, M. Altaf, S. S. R. Naqvi *et al.*, "A novel framework for rapid diagnosis of COVID-19 on computed tomography scans," *Pattern Analysis and Applications*, vol. 7, pp. 1–14, 2021.
- [10] N. Hussain, A. Majid, M. Alhaisoni, S. A. C. Bukhari, S. Kadry *et al.*, "Classification of positive COVID-19 CT scans using deep learning," *Computers, Materials and Continua*, vol. 66, no. 3, pp. 1–15, 2021.

- [11] M. U. Khan, S. Aziz, T. Akram, F. Amjad, K. Iqtidar *et al.*, “Expert hypertension detection system featuring pulse plethysmograph signals and hybrid feature selection and reduction scheme,” *Sensors*, vol. 21, pp. 247, 2021.
- [12] S. Zahoor, I. U. Lali, K. Javed and W. Mehmood, “Breast cancer detection and classification using traditional computer vision techniques: A comprehensive review,” *Current Medical Imaging*, vol. 4, pp. 1–21, 2020.
- [13] D. Poulikakos, K. Hnatkova, S. Skampardon, D. Green and M. Malik, “Sudden cardiac death in dialysis: Arrhythmic mechanisms and the value of non-invasive electrophysiology,” *Frontiers in Physiology*, vol. 10, pp. 144, 2019.
- [14] Cardiovascular diseases-Global facts and figures-World Heart Federation. 2017. [Online]. Available: <https://www.world-heart-federation.org/resources/cardiovascular-diseases-cvds-global-facts-figures/>. Last Accessed 21 March 2021.
- [15] K. A. Holst, S. M. Said, T. J. Nelson, B. C. Cannon and J. A. Dearani, “Current interventional and surgical management of congenital heart disease: Specific focus on valvular disease and cardiac arrhythmias,” *Circulation Research*, vol. 120, no. 6, pp. 1027–1044, 2017.
- [16] W. Xue, G. Brahm, S. Pandey, S. Leung and S. Li, “Full left ventricle quantification via deep multitask relationships learning,” *Medical Image Analysis*, vol. 43, no. 2, pp. 54–65, 2018.
- [17] M. Naz, J. H. Shah, M. Sharif, M. Raza and R. Damaševičius, “From ECG signals to images: A transformation based approach for deep learning,” *PeerJ Computer Science*, vol. 7, no. 1, pp. e386, 2021.
- [18] N. Mamorita, N. Arisaka, R. Isonaka, T. Kawakami and A. Takeuchi, “Development of a smartphone app for visualizing heart sounds and murmurs,” *Cardiology*, vol. 137, no. 3, pp. 193–200, 2017.
- [19] E. M. Cherry and F. H. Fenton, “Visualization of spiral and scroll waves in simulated and experimental cardiac tissue,” *New Journal of Physics*, vol. 10, no. 12, pp. 125016, 2008.
- [20] T. Ince, S. Kiranyaz and M. Gabbouj, “A generic and robust system for automated patient-specific classification of ECG signals,” *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 5, pp. 1415–1426, 2009.
- [21] J.-M. Belda-Lois, S. Mena-del Horno, I. Bermejo-Bosch, J. C. Moreno, J. L. Pons *et al.*, “Rehabilitation of gait after stroke: A review towards a top-down approach,” *Journal of Neuroengineering and Rehabilitation*, vol. 8, pp. 1–20, 2011.
- [22] Y.-C. Yeh and W.-J. Wang, “QRS complexes detection for ECG signal: The difference operation method,” *Computer Methods and Programs in Biomedicine*, vol. 91, no. 3, pp. 245–254, 2008.
- [23] B. Manju and M. Sneha, “ECG denoising using wiener filter and Kalman filter,” *Procedia Computer Science*, vol. 171, pp. 273–281, 2020.
- [24] K.-P. Lin and W. H. Chang, “QRS feature extraction using linear prediction,” *IEEE Transactions on Biomedical Engineering*, vol. 36, no. 10, pp. 1050–1055, 1989.
- [25] D. A. Coast, R. M. Stern, G. G. Cano and S. A. Brillner, “An approach to cardiac arrhythmia analysis using hidden Markov models,” *IEEE Transactions on Biomedical Engineering*, vol. 37, no. 9, pp. 826–836, 1990.
- [26] F. Jager, “Feature extraction and shape representation of ambulatory electrocardiogram using the Karhunen–Løeve transform,” *Electrotechnical Review*, vol. 69, pp. 83–89, 2002.
- [27] I. Clark, R. Biscay, M. Echeverria and T. Virués, “Multiresolution decomposition of non-stationary EEG signals: A preliminary study,” *Computers in Biology and Medicine*, vol. 25, no. 4, pp. 373–382, 1995.
- [28] A. Rezaei, A. Koulouri and S. Pursiainen, “Randomized multiresolution scanning in focal and fast E/MEG sensing of brain activity with a variable depth,” *Brain Topography*, vol. 33, no. 2, pp. 161–175, 2020.
- [29] S. Saxena, A. Sharma and S. Chaudhary, “Data compression and feature extraction of ECG signals,” *International Journal of Systems Science*, vol. 28, no. 5, pp. 483–498, 1997.
- [30] A. Kumar, R. Ranganatham, S. Singh, R. Komaragiri and M. Kumar, “A robust digital ECG signal watermarking and compression using biorthogonal wavelet transform,” *Research on Biomedical Engineering*, vol. 37, no. 1, pp. 79–85, 2021.

- [31] Q. Zhao and L. Zhang, "ECG feature extraction and classification using wavelet transform and support vector machines," in *2005 Int. Conf. on Neural Networks and Brain*, NY, USA, pp. 1089–1092, 2005.
- [32] S. Barro, R. Ruiz, D. Cabello and J. Mira, "Algorithmic sequential decision-making in the frequency domain for life threatening ventricular arrhythmias and imitative artefacts: A diagnostic system," *Journal of Biomedical Engineering*, vol. 11, no. 4, pp. 320–328, 1989.
- [33] R. Panda, S. Jain, R. Tripathy and U. R. Acharya, "Detection of shockable ventricular cardiac arrhythmias from ECG signals using FFREWT filter-bank and deep convolutional neural network," *Computers in Biology and Medicine*, vol. 124, no. 3, pp. 103939, 2020.
- [34] N. V. Thakor, Y.-S. Zhu and K.-Y. Pan, "Ventricular tachycardia and fibrillation detection by a sequential hypothesis testing algorithm," *IEEE Transactions on Biomedical Engineering*, vol. 37, no. 9, pp. 837–843, 1990.
- [35] F. Nawaz, M. Ramzan, K. Mehmood, H. U. Khan and M. R. Bhutta, "Early detection of diabetic retinopathy using machine intelligence through deep transfer and representational learning," *Computers, Materials and Continua*, vol. 66, no. 2, pp. 1631–1645, 2021.
- [36] F. Yaghoubi, A. Ayatollahi and R. Soleimani, "Classification of cardiac abnormalities using reduced features of heart rate variability signal," *World Applied Sciences Journal*, vol. 31, pp. 1–12, 2009.
- [37] H. M. Rai and A. Trivedi, "ECG signal classification using wavelet transform and back propagation neural network," in *2012 5th Int. Conf. on Computers and Devices for Communication*, NY, USA, pp. 1–4, 2012.
- [38] A. L. Goldberger, L. A. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov *et al.*, "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, pp. e215–e220, 2000.