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Article

Statistical Signal Processing and Machine Learning Based Diagnosis of Arrhythmia

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Abstract: The present work deals with the detection and classification of arrhythmia based on the analysis of an Electrocardiogram (ECG) signal. ECG signals have been collected from normal healthy persons and patients suffering from arrhythmia. Continuous Wavelet transform (CWT) and Discrete Wavelet transform (DWT) based statistical parameters are computed on the denoising ECG signals. In CWT analysis distinctive features have been computed for arrhythmia patients over normal healthy people. In this work Sinus Arrhythmia, Ventricular tachycardia (3 beats and 7 beats), Sinus bradycardia, Bidirectional ventricular tachycardia, Premature Ventricular Contractions types of Arrhythmia has been used. Clear differences in mean values and standard deviations for approximation and detail coefficients in DWT analysis have been noticed in both the cases. All these feature patterns and statistical analyses are used to diagnose arrhythmia. Then arrhythmia has been classified by different machine learning (ML) based techniques where maximum accuracy has been achieved in Random Forest and k-nearest neighbor (KNN) methods. Several cases have been considered to validate the proposed method where each and every cases result has obtained very much optimistic.

Keywords: Electrocardiogram; CWT; DWT, standard deviation; arrhythmia; SG filter

1. Introduction

Detection of cardiovascular (cardiac) disease at early stage is utmost required and by analysis of Electrocardiogram (ECG) signal, detection of cardiovascular diseases is an emerging field of biomedical research [1]. Generally, Electrocardiogram (ECG) signal is used for clinical finding in cardiovascular health. It is simple and non-invasive in nature. ECG is a graph of voltage vs. time which represents function of electrical activity of human heart as depicted in Figure 1. Electrodes ascertain and capture electrical signals by converting the bioelectrical activity produced by the myocardium during its contraction and relaxation stages, which play a crucial role in moving blood throughout the circulatory system [2]. ‘Any type of disorder or abnormality in the normal activation sequence of the myocardium is called cardiac arrhythmias’ [3]. For ECG diagnosis, 12 leads are mainly used where 10 electrodes are applied on different body parts and one of them used as a reference to others [3]. There are mainly 3 important waves indicate the heart’s three different electrical occurrence in one cardiac cycle: P wave (atrial depolarization), QRS complex wave (ventricular depolarization) and T wave (repolarization).

P Wave: P Wave represents Atrial Depolarization. During this two Atria are contracting.
Q Wave: The wave represents first negative deflection in the signal.
R Wave: It represents first positive deflection in the ECG.
S Wave: After R wave next negative deflection is S wave.
T Wave: Clinicians can learn vital information about the electrical stability of the heart from the T wave.

T-wave abnormalities can be used to determine: a) Arrhythmias: Changes in T wave shape can result from irregular heartbeats, b) Electrolyte imbalances: The form and timing of the T wave are directly impacted by blood levels of potassium, calcium, and sodium, c) Cardiac Ischemia: As previously indicated, T wave abnormalities (flattening or inversion) may indicate decreased blood supply to the heart muscle, which may ultimately result in a heart attack.

PR interval: Time interval during which depolarization wave travels from atria to ventricles.
QRS Complex: It represents Ventricular Depolarization.
ST Segment: It represents the duration between ventricular depolarization and the next repolarization.
QT Interval: It represents total ventricular heart activity.

Here for clinical purpose QRS complex and PR interval are important. T wave analysis is not required as it comes under relaxation part. Desired PR signal interval is 0.12–0.20 s, QRS complex interval is 0.06-0.12 s. Measuring R-R distance is important for interpreting an ECG strip. Shape of an abnormal QRS varies from almost normal to wide and bizarre/slurred. Tall QRS are mainly for hypertrophy of one/ both ventricles whereas short QRS means small voltage appeared in those who are obese and hyperthyroid. Any type of disorder or abnormality in the normal activation sequence of the myocardium is called cardiac arrhythmias. The simple meaning of arrhythmia is out of rhythm and arrhythmia mainly causes when the electrical signals that coordinate heart beats are not working properly. When the normal pumping mechanism of heart becomes irregular, arrhythmia appears in ECG signal. ECG displays the overall electrical activity of heart in the waveform. Arrhythmia can happen in any age group. Some arrhythmias are non-life-threatening but can cause severe complications if they are highly irregular.

Based on their origin (ventricular or atrial) and how they affect heart rate (tachycardia or bradycardia), they are generally categorized [4,5]. The main categories are a) Bradyarrhythmia (Slow Heart Rhythms), b) Tachyarrhythmia (Fast Heart Rhythms), c) Premature Heartbeats, d) Long QT Syndrome (LQTS).

Tachycardia and Bradycardia refer those conditions of heart rate which are too fast and too slow respectively. Tachycardia means over 100 beats/min while bradycardia means 60 or less beats per minute. Premature contraction beat is common and usually non-life-threatening. Supraventricular arrhythmias are tachycardias that occur in the AV node. Types of Supraventricular arrhythmias are Atrial Fibrillation, Atrial flutter, Paroxysmal Supraventricular tachycardia, Wolff-Parkinson-white Syndrome (a type of PSVT causing the ventricles to beat too fast). Ventricular arrhythmias are life threatening and types of Ventricular arrhythmias are Ventricular tachycardia, Ventricular fibrillation [4].

To detect the arrhythmia different methods, exist in the literature [6–8]. All the methods consist of 3 important steps first work with different pre-processing method, then feature extraction and the last step is classification. Some of recent works on arrhythmia detection are [8–12].

Discrete Wavelet transform (DWT) is a popular tool for time–frequency analysis. It is widely used in analysis of ECG signals. In [13] authors presented a DWT based technique to detect the QRS complex and arrhythmia. They have worked with MIT/BIH Arrhythmia database and it is reported that their method provides 0.221% detection error rate. Li, Taiyong, and Min Zhou [14] presented a ECG signal classification technique by combining the wavelet packet and entropy. They have worked on the MIT–BIH Arrhythmia database and checked the influence of different mother wavelets and the importance of various levels of decomposition. A. Dliou et al. [15] reported a non-parametric time-frequency technique for the classification of ECG arrhythmia. They have reported four different distribution techniques [15] which are Wigner–Ville distribution, the Choi–William's distribution, Born–Jordan distribution and Bessel distribution for the discrimination of ECG signal. Among these four techniques they have shown that Choi–Williams provides superior performance compared to others distribution. Other recent works on ECG based heart disease detection techniques are [16–18]. In [16] authors reported a machine learning (ML) based heart disease detection technique by analysing the ECG signal. They have used Support Vector Machine (SVM), K-Nearest Neighbours (k-NN), Random Forest, Extra Tree, Bagging, Decision Tree, Linear Regression, and Adaptive Boosting ML algorithm for the classification. Murugappan, M et al. [17] presented a Morphological Feature based Sudden Cardiac Arrest (SCA) Prediction technique by analysing the ECG signal. This method [Arabian 3] method provides the average accuracy of 100% for SVM classifier. In [18], along with LSTM, angle transform (AT) has been used for analysis In AT, angular information from the neighbouring signals on both sides the target signals has been utilised for classification purpose of ECG signals.In [19], arrhythmia classes have been classified by 'end to end 1-D convolutional neural network' where 'RRR (i.e., retaining ECG data between the R peaks just before and after the current R peak)' approaches have been used for ECG signal segmentation purposes.'1D Self organized Operational Neural Networks (1D Self-ONNs)' based approach is used in [20] to detect and classify arrhythmia, where authors used practical data to verify their proposed approach.Deep learning techniques, such as CNN, LSTM etc. have been used for classification of arrhythmia where authors used MIT-BIH database to validate their methods [21,22].

None of the discussed techniques used statistical signal processing along with Machine Learning

(ML) approaches for detection and classification of arrhythmia. The novelty of this work is that, ECG signals firstdenoised by SG filter then it is normalized from which statistical parameters (standard deviation, mean etc.) have been estimated based on DWT technique to detect arrhythmia. Then different ML techniques have been used for classification of arrhythmia.

The rest portion of this work has been structured as follows. Section 2 describes mathematical tools used to detect arrhythmia, Section 3 narratespre-processing and feature extraction from ECG signal, section 4 discusses results and discussions and Section 5 is the conclusion of this work.

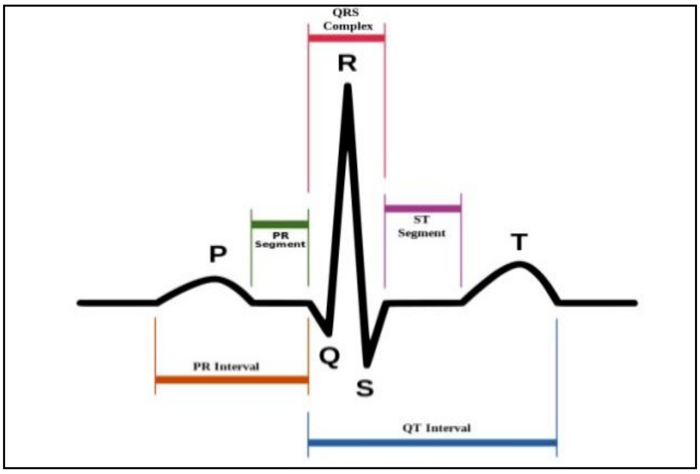

Figure 1.ECG Signal [2].

2. Mathematical Tools Used for Arrhythmia Detection

In this proposed work, to detect the arrhythmia, CWT, DWT and statistical parameters like standard deviation, mean have been considered. After DWT, statistical parameters have been calculated to detect arrhythmia. CWT and DWT is used to extract the time-frequency information of a signal. ECG signal is inherently non-stationery in nature. CWT and DWT is compatible to extract the time-frequency information from a non-stationery signal. 'dB4' is used as mother wavelet for this analysis. CWT is basically the convolution of two functions. One is input sequence, and another is mother wavelet. CWT gives the three-dimensional results in terms of scale (1/frequency), translational value (1/time), and coefficients. The CWT of a signal y(t) can be explained as,

$$Y_{\omega}(c,d) = \frac{1}{|c|^{\frac{1}{2}}} \int_{-\infty}^{\infty} y(t)\varphi^{*}(\frac{t-d}{c})\, dt \tag{1}$$

In equation (1), 'c' represents scale,'d' represents translational value, $\varphi^{*}(t)$ is the complex conjugate of mother wavelet.The limitation of CWT is that; it generates lots of data for analysis. For this reason, statistical parameters have been estimated from DWT analysis, though changes in CWT for arrhythmia cases are also clear with respect to healthy ECG.

To represent discrete signal in more redundant form, DWT is used. In DWT, the signal is passing through a filter bank. Filter bank consists of two filters. One is high pass filter, and another is low pass filter. Output of high pass filter is named as detail level coefficients which contains higher order harmonics. Output of low pass filter is called approximate coefficients which contains lower order harmonics. In this method, each DWT decomposition level approximation coefficients have been further decomposed to extract detail and other approximation coefficients in next level. Nine (9) level of decomposition has been done here to detect arrhythmia. As the arrhythmia ECG signal contains of different frequencies, so to extract the different frequency band for computation of statistical parameters like mean and standard deviation for each frequency band, DWT is used here. In DWT, signal decomposed is depicted in figure below. Here three level DWT decomposition is shown though in this work signal is decomposed in nine levels to get better information. In Figure 2, d represents detail component and a represents approximation or approximate coefficients. If a discrete signal is defined by y(n), then after DWT, output of low pass filter and output of high pass filter can be written as,

$$x_{low}(n) = \sum_{k=-\infty}^{\infty} y[k]h[2n-k] \tag{2}$$

$$x_{high}(n) = \sum_{k=-\infty}^{\infty} y[k]g[2n-k] \quad (3)$$

where, h and g are the low pas and high pass filter respectively.

In statistical analysis [23], mean indicates the equal distribution of data in a data set. Central tendency of distribution is measured by mean. Mathematically mean is the mean value of a given data set. If $y_1, y_2, \dots, y_n$ are the n numbers of discrete values, then mean can be computed using the following given formula:

$$\bar{y} = (y_1 + y_2 + \cdots + y_n)/n \quad (4)$$

where $\bar{y}$ represents mean of the values and n represents number of values. Standard Deviation is the dispersion of data from its average value. Standard deviation can be calculated from the following formula:

$$z = \sqrt{\frac{\sum_{i-1}^{n}(y_i - y_m)^2}{N}} \quad (5)$$

where, z is the standard deviation, $y_i$is each population value, $y_m$represents mean value of data and N is the population size.

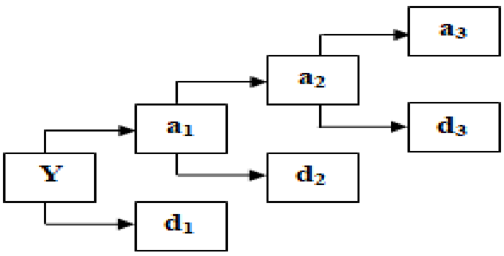

Figure 2.DWT decomposition.

3. Pre-Processing of Electrocardiogram Signal for Feature Extraction

In this proposed method, ECG signal of normal healthy person and arrhythmia cases have been considered. At first, in both the cases, the collected ECG signals have been fed through a SG FIR filter for de-noising. In real life, ECG signals are polluted or corrupted by different noises like 'baseline wander', 'Gaussian noise', 'power line interference' etc. due to external reasons or psychological behaviours of human body. From the corrupted ECG signal, extraction of clean ECG signal is known as denoising [24]. In this work Savitzky-Golay (S-G) filter is used for denoising purpose. Linear least-squares method is used in S-G filter. It is a finite impulse response (FIR) non-causal smoothing filter that can smooth the data by fitting successive sub-sets of adjacent data points with low polynomial degree. The S-G filter has the advantage of effectively maintaining the signals high frequency components without compromising its original characteristics [25]. After de-noising, ECG signals are used for further processing. CWT and DWT based standard deviations, mean values are computed in both the cases. Comparing the results, arrhythmia has been detected. The flow diagram of the proposed technique is shown in Figure 3.

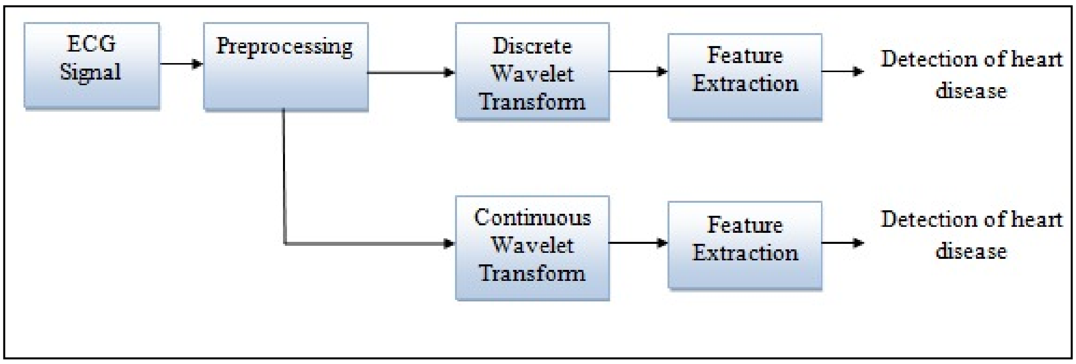

Figure 3. Flow diagram of proposed method.

ECG signal of normal healthy person and patient suffering from arrhythmia has been considered for analysis. ECG of normal healthy person which is depicted in Figure 4 has been de-noised by passing through a Savitzky-Golay (SG) finite impulse response filter (FIR). De-noised ECG beats are normalized for analysis which is delineated in Figure 5. In similar way, ECG of arrhythmia patient has also been analysed. ECG of arrhythmia patient which is depicted in Figure 6 has also been de-noised by passing through a SG FIR filter. De-noised ECG signal of arrhythmia patient has been normalized for analysis as shown in Figure 7. In both the cases denoising has been done up to level fifteen (15) of SG FIR filter for smoothening of ECG signal.

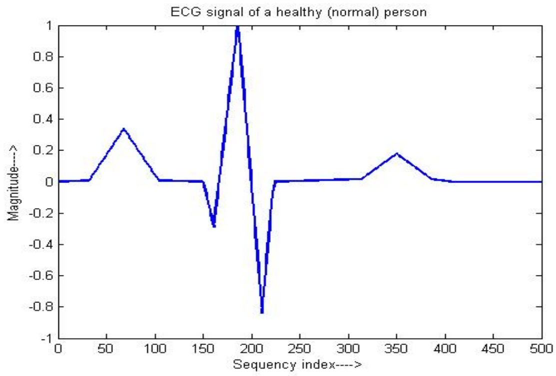

Figure 4. ECG of normal healthy person.

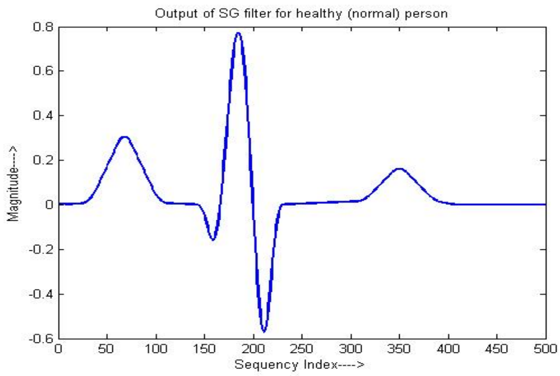

Figure 5. De-noised and normalized ECG of normal healthy person.

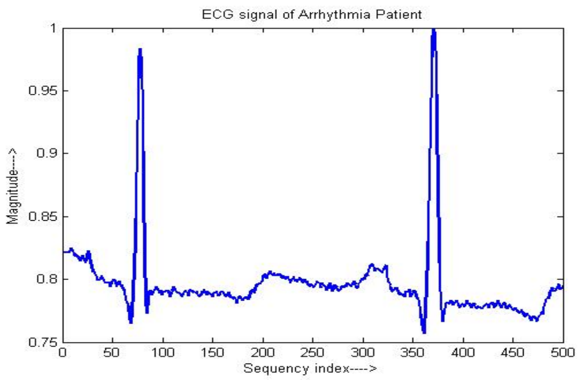

Figure 6. ECG of arrhythmia patient.

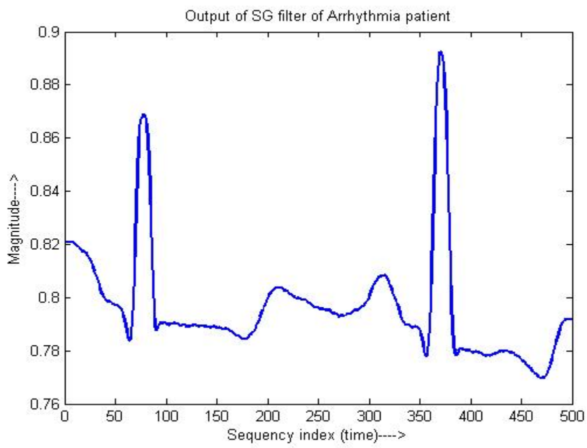

Figure 7. De-noised and normalized ECG.

4. Results and Discussions

4.1. Used Dataset

In the proposed work MIT-BIH Arrhythmia Database has been used. It contains 48 half-hour segments of two-channel ambulatory ECG recordings from 47 patients [26]. We have worked with Sinus Arrhythmia, Ventricular tachycardia 3 beats, Ventricular tachycardia 7 beats, Sinus bradycardia, Bidirectional ventricular tachycardia, Premature Ventricular Contractions types of Arrhythmia.

4.2. CWT Assessment of ECG for Arrhythmia Detection

CWT is utilized, here for the detection of arrhythmia. CWT has been done on the captured ECG signals of normal healthy person and the patient suffering from arrhythmia. Figure 8 and Figure 9 are used to depict the CWT result of de-noised ECG signal of normal healthy person and arrhythmia patient respectively. In Figure 8, maximum value of sub harmonics is more than two (2) whereas in Figure 9 it is with in between 1 to 1.5. Maximum deviation is noticed in one time in Figure 8, whereas in Figure 9 maximum deviation is observed two times. So, magnitude and time of coefficient values of CWT result can be utilized for the arrhythmia detection.

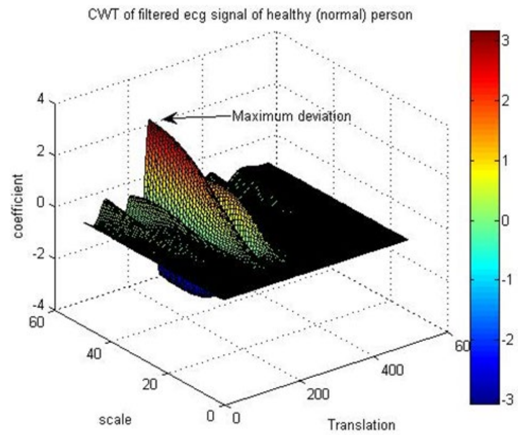

Figure 8. CWT of de-noised ECG of normal healthy person.

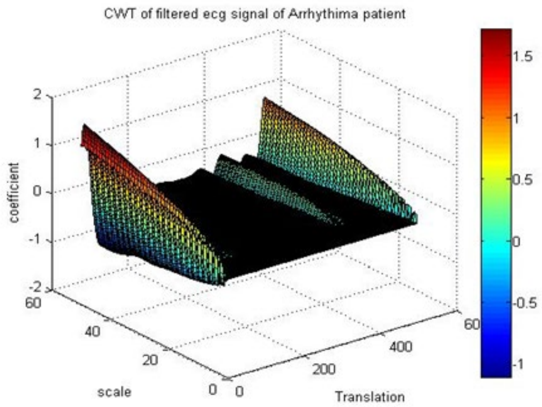

Figure 9. CWT of de-noised ECG of arrhythmia patient.

4.3. DWT Based Statistical Parameter Analysis for Arrhythmia Detection

Here DWT has been done on the de-noised and normalized ECG signal and statistical parameters such as standard deviation and mean value has been computed to detect the arrhythmia. In this analysis, 'dB4' is applied as mother wavelet and ECG signal is decomposed up to DWT decomposition level 9. In each level, standard deviation and mean or average value has been computed on approximation and detail coefficients of DWT decomposition. Sample of DWT coefficients (Detail and Approximation) of normal ECG signal and arrhythmia (Sinus Arrhythmia) case (up to 3rd level decomposition) are depicted in Figure 10 and Figure 11 respectively.

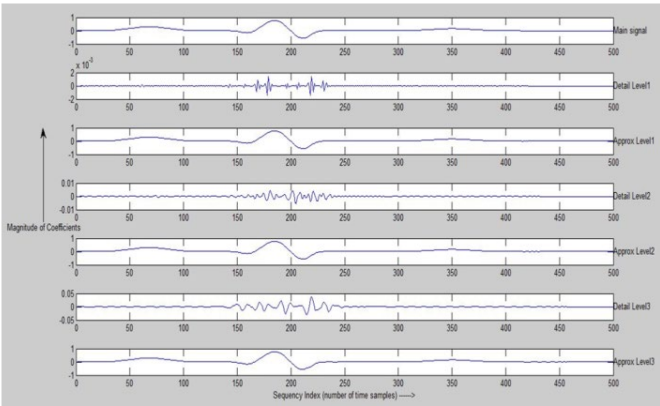

Figure 10. Sample of DWT coefficients (Detail and Approximation) of normal ECG signal up to 3rd level decomposition.

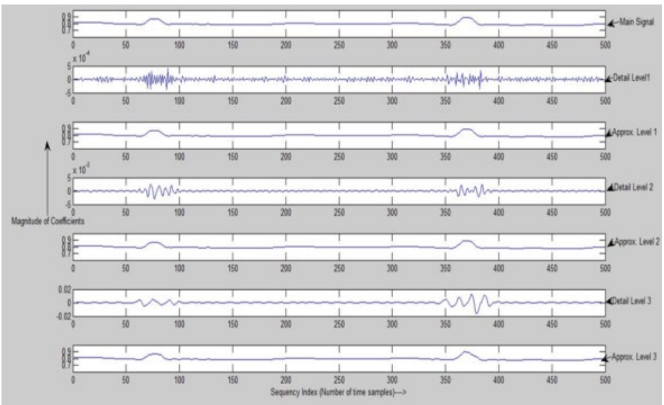

Figure 11. Sample of DWT coefficients (Detail and Approximation) of ECG signal of arrhythmia patient up to 3rd level decomposition.

Figure 12 delineates the result of mean values of approximation coefficients. For normal healthy person it is almost zero but for arrhythmia patient the value is 0.8. Figure 13 depicts the result of mean values of detail coefficients. In Figure 13, up to DWT decomposition level five (5) values are same for both the cases but the deviations of mean vales are started from DWT decompositionlevel-6. Deviation is maximum in DWT decomposition level 9. Using these values, arrhythmia can be detected easily.

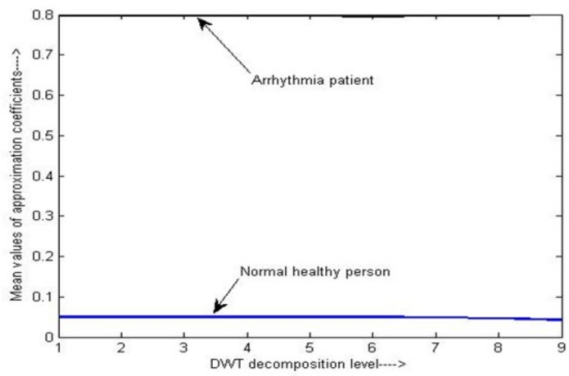

Figure 12. Mean values of approximation coefficients for arrhythmia patient and normal person.

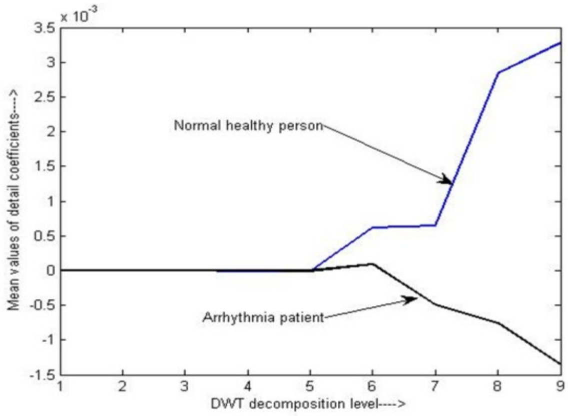

Figure 13. Mean values of detail coefficients for arrhythmia patient and normal person.

In Table 1, mean values of detail and approximation coefficients have been delineated of a normal healthy person. For approximation coefficients, maximum mean values have been recorded at DWT decomposition level five (5), whereas for detail coefficients, it is maximum at DWT decomposition level nine (9). Table 2 shows the mean values of approximation and detail coefficients of arrhythmia patient. For approximation and detail coefficients maximum mean values have been noticed at DWT decomposition level nine (9) and six (6), respectively. Figure 14 depicts the standard deviations of approximation coefficients and Figure 15 shows the standard deviations of detail coefficients for arrhythmia patient and normal person. Standard deviations of approximation and detail coefficients up to DWT level nine of normal healthy person is mentioned in Table 3 and for arrhythmia patient is mentioned in Table 4. In Figure 14 differences between healthy ECG and arrhythmia case is maximum upto decomposition level four (4) where as differences of standard deviations of detail coefficients between healthy person and arrhythmia case is maximum in between decomposition level four (4) to seven (7) which is shown in Figure 15.

Table 1. Mean values of approximation and detail coefficients up to DWT level nine of normal healthy person.

DWT Decomposition Level	Mean Values of Approximation Coefficients	Mean Values of Detail Coefficients
1	0.050197	-3.40×10^{-23}
2	0.050197	-1.05×10^{-08}
3	0.050197	2.74×10^{-08}
4	0.0502	-3.02×10^{-06}
5	0.050207	-7.36×10^{-06}
6	0.049592	0.000615
7	0.048949	0.000643
8	0.046104	0.002844
9	0.042817	0.003287

Table 2. Mean values of approximation and detail coefficients up to DWT level nine of arrhythmia patient.

DWT Decomposition Level	Mean or Average Values of Approximation Coefficients	Mean or Average Values of Detail Coefficients
1	0.796517	-2.20×10^{-20}
2	0.796517	4.50×10^{-09}
3	0.796518	-8.74×10^{-07}
4	0.796517	1.02×10^{-06}
5	0.796522	-4.70×10^{-06}
6	0.796432	8.96×10^{-05}
7	0.796928	−0.0005
8	0.797687	−0.00076
9	0.799039	−0.00135

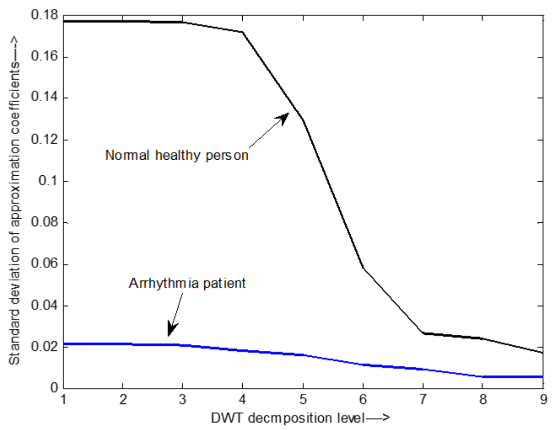

Figure 14. Standard deviations of approximation coefficients for arrhythmia patient and normal person.

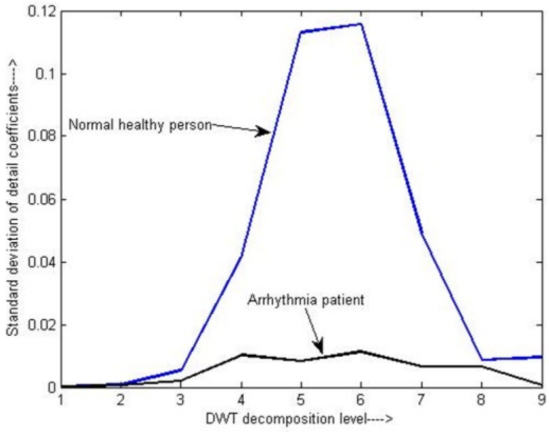

Figure 15. Standard deviations of detail coefficients for arrhythmia patient and normal person.

Table 3. Standard deviations of approximation and detail coefficients up to DWT level nine of normal healthy person.

DWT Decomposition Level	Standard Deviations of Approximation Coefficients	Standard Deviations of Detail Coefficients
1	0.176864	0.000173
2	0.176862	0.000821
3	0.176779	0.005411
4	0.171872	0.041359
5	0.129449	0.113041
6	0.058268	0.115717
7	0.026497	0.049235
8	0.024156	0.008614
9	0.017054	0.009517

Table 4. Standard deviations of approximation and detail coefficients up to DWT level nine of arrhythmia patient.

DWT Decomposition Level	Standard Deviations of Approximation Coefficients	Standard Deviations of Detail Coefficients
1	0.021064	0.000074
2	0.021057	0.000564
3	0.020964	0.001974
4	0.018250	0.010313
5	0.016190	0.008389
6	0.011174	0.011348
7	0.009297	0.006590
8	0.005734	0.006628
9	0.005387	0.000652

Figure 16 and Figure 17 depicts the mean values and standard deviations of approximation coefficients respectively for healthy person and different arrhythmia cases. These values are average values of different cases. In Figure 16, clear differences are observed between healthy person and seven (7) types of arrhythmia cases throughout the all DWT decomposition levels, where as in Figure 17, differences are clear upto DWT decomposition level seven (7). These all values have been further used in different machine learning (ML) algorithms to finally detect different arrhythmia cases (seven types).

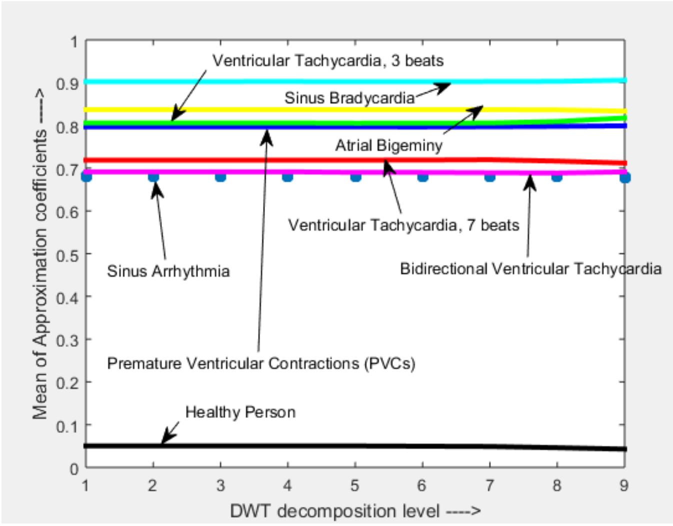

Figure 16. Mean of approximation coefficients of healthy person and different arrhythmia cases.

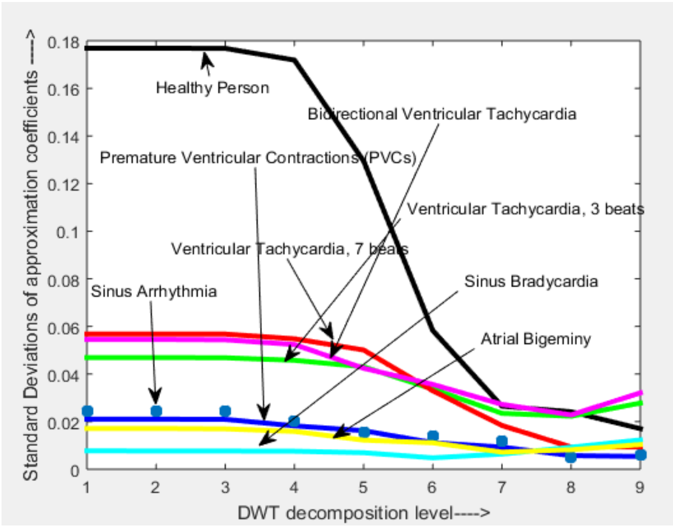

Figure 17. Standard deviationof approximation coefficients of healthy person and different arrhythmia cases.

Findings of arrhythmia analysis by statistical signal processing have been given in Table 5. Performance metrics are computed on the mean value and standard deviation of approximation and detail coefficients using Naïve Bayes, Multilayer Perceptron Model, Support Vector Machine, Decision Table, K-Nearest Neighbour, J48, Adaboost, Random forest classifier. Table 6 is used to depict the performance of the above mentioned techniques. Comparative study of the existing research has been delineated in Table 7; from there acceptability of the proposed technique can be justified

Table 5. Statistical Signal Processing results in a nutshell.

Parameters	**Analysis of Findings**
Mean of Detail Coefficients	Maximum value is observed as 0.003287 for healthy person. For arrhythmia, maximum value is 0.00008
Mean of Approximation Coefficients	For healthy person, maximum value of detail coefficients has been observed as 0.05 where as for arrhythmia case its maximum value is 0.79.
Standard Deviation of Detail Coefficients	Maximum value for healthy person is 0.11 but for arrhythmia is 0.01
Standard Deviation of Approximation Coefficients	For arrhythmia, maximum value is 0.02, whereas for normal case maximum value is0.17

Table 6. Performance of 5-fold cross validation technique.

Classifier	**Accuracy (for mean of the coefficients**	**Accuracy(for standard value of the coefficients**
Naïve Bayes	70.3704 %	94.7368 %
Multilayer Perceptron Model	68.5185 %	91.2281 %
Support Vector Machine	74.0741 %	77.193 %
Decision Table	99.34%	91.2281 %
K-Nearest Neighbour	99.35%	94.7368 %
J48	96.2963 %	91.2281 %
Adaboost	53.7037 %	52.6316
Random forest	99.35%	94.7368 %

Table 7. Comparative study with other existing methods.

Reference	**Year**	**Method**	**Accuracy**
18	2020	1D CNN	99.24%
19	2021	1D Self-Operational Neural Networks	99.04%
20	2018	deep convolutional neural networks	93.40%
21	2023	11-layer CNN model and Long Short-Term Memory (LSTM)	94.10%
Proposed method	-	Wavelet transform+ Statistical Analysis+ Machine Learning	99.35%

5. Conclusions

In this work, electrocardiogram (ECG) signal has been assessed to detect the arrhythmia disease. CWT, DWT based statistical parameter is computed from ECG signals of normal healthy person and patient suffering from arrhythmia. In CWT, distinct features have been extracted for arrhythmia patient over normal healthy person. In DWT based standard deviations and mean value analysis, clear differences have been noticed for approximation and detail coefficients. Constant differences have been detected for mean values approximation coefficients in two conditions. Mentioned statistical parameters further used in different machine learning (ML) techniques for classification of arrhythmia cases. The proposed method (statistical signal processing with ML) and results can be utilized for clinical diagnosis of arrhythmia. The proposed work can be extended as follows:

i)The importance of other statistical parameters of ECG signal can be analyzed.
ii) An optimized framework can be designed to select the important features.
iii) Importance of features can be studied using Explainable AI.

Author Contributions

A.C., S.B. and S.R. developed the method and performed the analysis and wrote the manuscript. N.D.J. and D.R., A.M. check the manuscript and N.D.J. A.M. also reviewed the manuscript. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

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