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Electrocardiogram Diagnosis Using SVM

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Abstract: *The electrocardiogram (ECG) represents one of the most essential biological signals and plays a crucial role in the initial diagnosis and survival analysis of heart illnesses. In this research, an automated ECG interpretation system is developed to detect and diagnose cardiac arrhythmia of four types. The proposed system is implemented under the MATLAB environment, being applied on a set of 46 ECG records with a total duration of 23 hours; these records are taken from the online MIT-BIH database. ECG signal segmentation, using Wavelet transform, generates the features for each heartbeat. Utilizing the generated features alongside Principal Component Analysis (PCA) for features reduction and Support Vector Machine (SVM) for classification, the proposed system successfully achieved good results compared with similar works in the same research field. The results show that the diagnostic accuracy of the left bundle branch block beat (LBBB) is 97.5%, while the accuracy of the right bundle branch block beat (RBBB) is 97.0%. In the other hand, the accuracy of the premature ventricular contraction (PVC) and the normal beat is 94.5% and 95.0%, respectively.*

Keyword: *ECG; Wavelet; PCA; SVM; Classification*

1. INTRODUCTION

The ECG, which stands for electrocardiogram, is among the most significant physiological or biomedical signals; it is a graphical illustration of heart rhythms and is utilized to analyze different heart issues and abnormalities. Willem Einthoven was the first to record the ECG signal in 1902 using a crude galvanometer; the ECG measurement was enhanced, but the principles are still the same[1]. The electrocardiogram signal is a non-stationary signal that measures the heart's activity. In general, it contains three waves or components P, QRS, and T. Every wave indicates a different type of cardiac action. The P wave is the first ECG wave that records the period of atrial depolarization, then the QRS wave recorded, which records the duration of ventricular depolarization. Finally, the T wave records ventricle repolarization, which comes after the QRS complex [2]. Figure 1 illustrates a typical ECG Waveform.

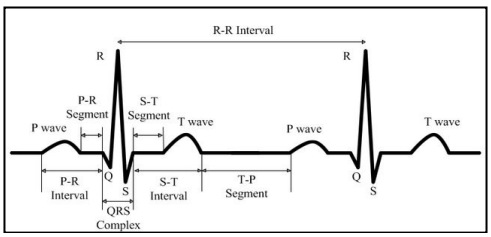

Figure 1. A typical cardiac waveform[3]

The ECG signal, as mentioned above, consists of five basic components or waves P, Q, R, S, and T wave; Every wave indicates a different type of cardiac action. The ECG component is as stated below: -

A. The p wave is the first ECG wave of the cardiac cycle, demonstrating atria's activation; it is generated from the SV node causing atrial contraction. The average P wave duration is nearly 10^{-1} sec-

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onds, while the voltage range (10^{-1} to $3x10^{-1}$) mV [4].

B. QRS Complex is the second ECG wave, which is the most significant component in the electrocardiogram signal; this wave records ventricle contraction. This large wave appears to have several components, Q, R, and S. The first component is the Q wave, a tiny (-ve) component with a mean voltage range ($6x10^{-2}$ to $19x10^{-2}$) mV. The R wave is the tallest wave in the electrocardiogram and has a voltage range ($5x10^{-1}$ to $18x10^{-1}$) mV. S component is the next downward deflection of QRS, whose voltage value is nearly $4x10^{-1}$ mV in the (-ve) direction, the QRS duration for a normal person range is ($8x10$ to 10^2) ms [5].

C. T Wave records ventricle diastole; it lasts for around $27x10^{-2}$ seconds, and its voltage range ($15x10^{-2}$ to $5x10^{-1}$) mV. The area of the T wave is really helpful for detecting a cardiac disease related to the ventricle [6].

D. PR segment is the flat isoelectric portion that exists between both the ending point of the P wave and the starting point of the QRS wave; it occurred due to the delay of the electrical impulse at the AV node to allow for atrial contraction [7].

E. PR interval is the time elapsed between the P wave's starting point and the QRS wave's starting point. It describes the interval between the starting point of atrial contraction and the starting point of ventricular contraction. The PR period normally lasts between ($12x10^{-2}$ to $2x10^{-1}$) seconds. [7].

F. ST Segment is the flat portion, the isoelectric portion of the ECG between both the last point of the S wave and the first point of the T wave; the ST segment indicates the delay time between ventricle contraction and ventricle diastole [8].

G. ST Interval is the period between both the shift of the QRS complex and the shift of the T wave. The ST period indicates the portion of the cardiac signal between ventricular depolarization and repolarization [8].

H. RR Interval is the period between two successive R waves. The RR period represents the amount of time between heartbeats, so it is useful to calculate the heartbeat rate; in a healthy person, it lasts for about ($6x10^{-1}$ to 1) second [9].

The peak of each wave component is evaluated according to the electrocardiogram baseline level, and its period is described by the two time instants at which the wave either departs significantly from or passes the baseline. The baseline is the straight line on the ECG tracing, representing an absence of electrical activity. The ECG signal can be considered normal or abnormal by evaluating the amplitudes and durations of these waves.

2. NORMAL AND ABNORMAL ECG SIGNAL

An electrocardiogram (ECG) is a diagnostic that determines whether or not the heart's electrical activity is normal. This section shows the normal ECG state and several abnormal states (heart arrhythmia):

A. Normal ECG Signal: A typical ECG signal does indeed have a pulse rate of (60 to 100) beats per minute (BPM) [10], and its waveform is close to that of a typical ECG signal, as illustrated in Figure 1.

B. Sinus tachycardia : Tachycardia is a pulse rate exceeding 100 beats per minute. Whenever the SA node beats more than 100 beats per minute, it causes sinus tachycardia. Sinus tachycardia is the usual reaction to sympathetic nervous system activation [11].

C. Sinus Bradycardia : Bradycardia is described as having a pulse rate that is less than 60 beats per minute. Sinus bradycardia can be a typical cardiac state for some people, such as sportsmen, or it can occur while sleeping [12].

D. Left Bundle Branch Block Beat: Left bundle branch block (LBBB) is a condition that occurs after the age of sixty years and is caused by a block in the passage in the bundle that receives impulses from the atrial and carries electrical current through the left ventricle. In LBBB, the QRS complex is odd and lasts longer than 120ms [13].

E. Right Bundle Branch Block Beat (RBBB): The right bundle branch is blocked impulses originating in the SA node or atria passing through the AV node to the ventricles. The impulse cannot pass through the right bundle branch, so it depolarizes the left ventricle first and then the right ventricle. In RBBB, the period of the QRS complex is wider than the normal QRS complex [14].

F. Premature ventricular contraction (PVC): A premature ventricular contraction (PVC) is a depolarization that originates in the ventricles. In the PVCs, there is no P wave, the R wave amplitude is increased, the QRS complex is wide (long duration), and the amplitude of the T wave increases opposite polarity [15].

3. THE PROPOSED APPROACH FOR HEARTBEAT CLASSIFICATION

An automated ECG heartbeat classification can be designed to decide whether the heartbeat is a normal

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heartbeat which means the heart works properly, or it is an abnormal heartbeat which indicates that the heart may not work properly. The automated ECG heartbeat classification is designed using four stages, as illustrated in Figure 2.

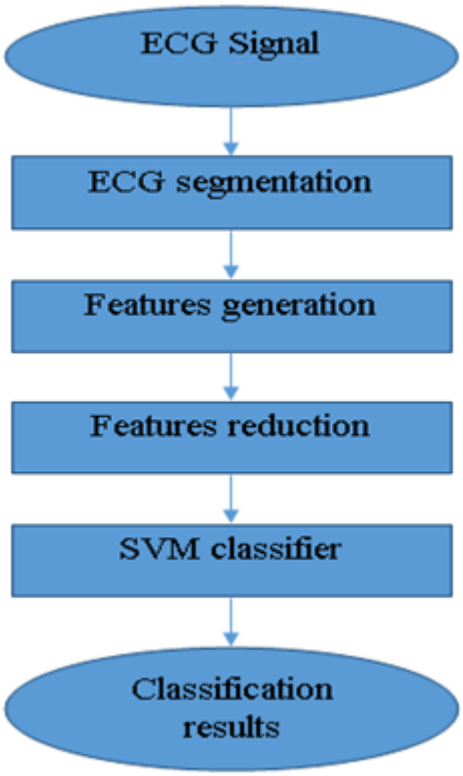

Figure 2 The proposed approach

The electrocardiogram signal is segmented via wavelet transform to detect the positions and peaks of P, QRS, and T waves in each heartbeat; this will help distinguish one heartbeat from another, which is also useful to generate features in the next step. The feature generation stage generates features based on P, QRS, and T, which the previous stage has detected; also, this stage generates features from wavelet transform coefficients for each heartbeat. The main goal of the feature reduction stage is to minimize the number of features created in the feature generation stage. The final stage is the classification stage.

There are many different classification methods for data. The most accurate classification method has not yet been identified for every type of data set. Support vector machine (SVM) is gaining popularity since it has a strong mathematics background and appears to work rather well in a variety of different real-world applications Support vector machine is an effective computational mathematical model for classification tasks. SVM is a controlled or supervised learning method utilized in the fields of classification and regression [16]. In this work SVM classifier which, according to the features coming from the features reduction stage, classifies the heartbeats as normal or abnormal of four types: LBBB, RRRB, PVC, and paced beat.

3.1 ECG Segmentation

Electrocardiogram segmentation is a slightly difficult task since the electrocardiogram is a time-varying signal subjected to biological variations caused by the patient and contamination caused by various noise sources. The wavelet transform could be an effective method for ECG segmentation, detecting P, Q, R, S, and T waves. Many wavelet families include Daubechies, Haar, Mexican hat, and others[17]. Daubechies family is chosen to be the wavelet basis function because it is similar to the QRS complex, and Low values of frequencies dominate its energy spectrum. [18].

The ECG segmentation can be done, similar to [18], using the algorithm in Figure 3. First, the R peak location is located, and the Q and S waves are located by seeking the minimum value of the signal before and after the R peak location; then, zero crossings are detected by searching for zero crossings before and after Q and S waves. Zero crossing is useful to determine the starting point and the last point of the QRS complex. Finally, the P and T waves are located by seeking the maximum signal value before and after the two zero-level points. The ECG signal is wavelet transformed for eight levels, then the details components at certain levels are used to detect different ECG signal parts, as summarized in Figure 3.

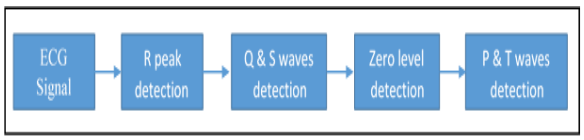

Figure 3 Stages of the ECG segmentation algorithm.

3.1.1 Detecting the R peak

Detection of the R peak can be done in three steps by using wavelet decomposition and reconstruction, squaring, and thresholding, as illustrated in Figure 4.

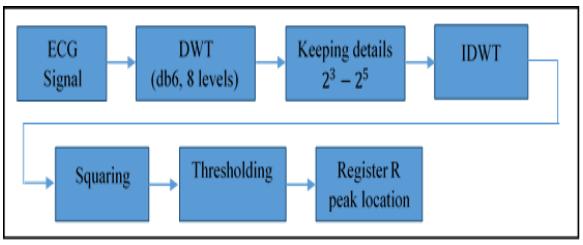

Figure 4 Block illustration of the algorithm for R peak detection

The Electrocardiogram signal, as illustrated in Figure 5, is decomposed by using wavelet transform with Daubechies6 function (db6) for eight levels, and then

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the signal is reconstructed by using inverse wavelet transform from only details of levels 3, 4, and 5. This operation will remove p and t waves from the Electrocardiogram signal and keep only the QRS complex, as illustrated in Figure 6.

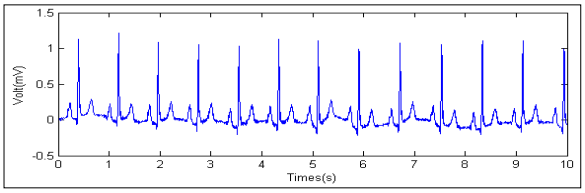

Figure 5 Electrocardiogram signal

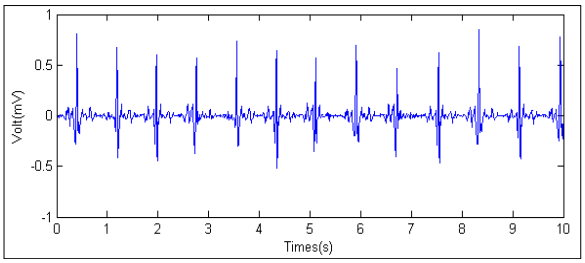

Figure 6 Reconstructed ECG signal after wavelet transform (db6, 8 levels, detail $2^3 - 2^5$).

The squaring process improves the outcome and emphasizes the significant disparities between QRS Complex and the tiny changes caused by P and T waves., so the P and T are suppressed, and the QRS complexes are more improved; the result of this operation is illustrated in Figure 7.

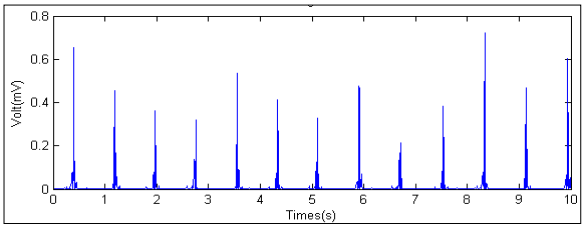

Figure 7 The Electrocardiogram signal after squaring.

The signal is compared with a threshold. If it is greater than the threshold and the distance from the previous R peak equals or exceeds $25x10^{-2}$ second, then the R peak location is registered, and the threshold is the average of the squared signal divided by two.

3.1.2 Detecting Q and S waves

The Q and S waves are the second segments that are to be extracted; the detection of these segments can be done by using: wavelet decomposition and reconstruction and seeking for the minimum value of the signal before the R peak to get the Q wave and after the R peak to get the S wave, as illustrated in Figure 8.

The ECG signal is decomposed by using the wavelet transform of Daubechies6 function (db6) for eight levels, and then the signal is reconstructed by using inverse wavelet transform from only details of levels 5, 6, 7, and 8. The wavelet transform manifests the Q and S waves while minimizing the P, R, and T waves. In this step, the locations, as well as the values of the Q and S waves, are found by seeking for minimum values of the signal with a duration of 100 msec; the minimum value before the R peak will be the Q wave, and the minimum value after the R peak will be the S wave.

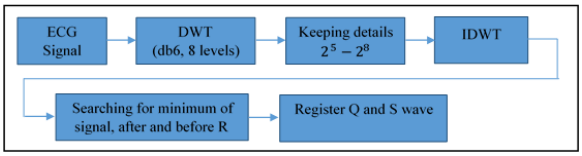

Figure 8 Block illustration of Q and S wave detection.

3.1.3 Detecting the zero levels

Zero level means that there is no current flow in the cardiac muscle; in this case voltage of the ECG signal must be 0V, but because the ECG signal is affected by noise resulting from skin potentials such as EOG, EEG, EMG, and other noises, it is very difficult to detect the exact zero level; instead, the zero level will be found approximately. The wavelet transform is used to find the zero levels, and then two points of zero level are to be located, as illustrated in Figure 9.

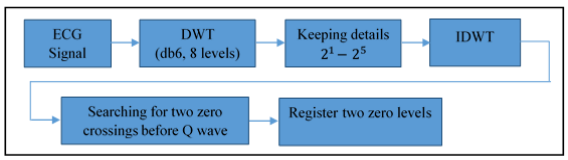

Figure 9 Block illustration of the zero crossing detection.

The ECG signal is decomposed utilizing wavelet transform (db6), and then the signal is reconstructed using 1, 2, 3, 4, and 5 details coefficients. The two zero levels are found by searching for the two minimum absolute values of the signal, one before the Q wave and the other after the S wave.

3.1.4 Detecting T and P waves

The T and P waves are found after zero-level detection. These waves are also detected by using the wavelet transform and then searching for the maximum two points after and before the two zero-level points, as illustrated in Figure 10.

The wavelet transforms decomposition and reconstruction for the 4, 5, 6, 7, and 8 details coefficients make the P and T waves more noticeable while attenuating the other ECG components. The P and T waves will be found by searching for a maximum signal value within durations less than $25x10^{-2}$ seconds before and after the two zero levels.

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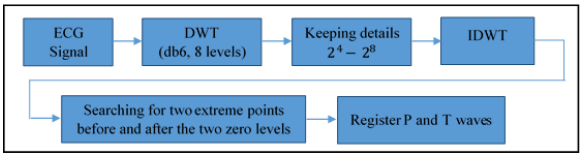

Figure 10 Block illustration of P and T wave detection

3.2 Features Generation

The main goal of this stage is to generate two groups of features. The first group of features is generated based on the positions and amplitudes of P, Q, R, S, and T waves which are detected in the previous stages; the 17 features group is generated as illustrated in Table I.

TABLE. I FEATURES DESCRIPTIONS FOR THE FIRST GROUP

Feature NO.	Description	Feature NO.	Description
1	X (P)	10	X (R2)
2	V (P)	11	V (R2)
3	X (Q)	12	V (R2) – V (R1)
4	V (Q)	13	X (T) – X (S)
5	V (R1)	14	X (P) – X (T)
6	X (S)	15	X (Q) – X (P)
7	V (S)	16	X (R2) – X (Q)
8	X (T)	17	X (S) – X (Q)
9	V (T)		

Where: R1 is the R peak value of the current heartbeat, R2 is the R peak value of the next heartbeat, X () means the position of each of the waves (P, Q, or …etc.) according to the position of R1, V () means the amplitude of each of the waves (P, Q, or …etc).

The second group of features is generated by taking 201 samples of the heartbeat signal at the center of the R peak, which means taking 100 samples before and after the R peak. Then these samples are used for the wavelet transform (db6, 8 levels) to get 283 wavelet coefficients which are considered as the features.

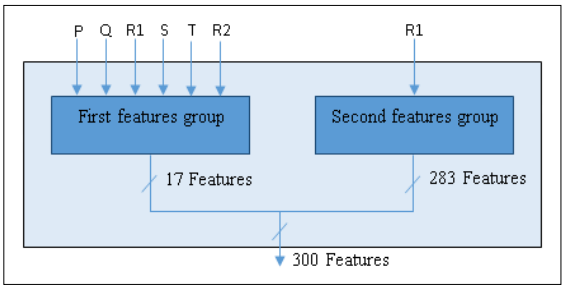

Figure 11 Block illustration of the features generation stage

So, this stage gives a feature vector of 300 elements, 17 feature elements based on P, Q, R, S, and T waves, and 283 feature elements which are the wavelet coefficients, as illustrated in Figure 11.

3.3 Features Reduction

Using 300 features to represent each ECG signal means forming a huge number of data for the diagnosis, which needs powerful processing for training and testing. This stage reduces the features vector from 300 to 20 elements. The Principal Component Analysis (PCA) is used to reduce the elements in the features vector to a minimum number and to produce uncorrelated features [19]. The feature reduction will be very useful in the classification stage to minimize the training and testing time, and the performance will increase because the features become uncorrelated. Only the first 20 elements of the principal component (the output of PCA), which contain 99.74% of the original feature vector, will be used for the classification stage.

3.4 Classification

Classification is the final stage in the cardiac arrhythmia diagnosis system, which is applied after the ECG segmentation, feature generation, and reduction. The classification stage aims to classify each heartbeat in the ECG signal according to its contents by comparison with the information acquired during the training phase. The classifier's performance is measured by specificity, sensitivity, and accuracy, as seen in equations 1, 2, and 3, respectively[20].

$$Specificity = \frac{TN}{TN+FP} \quad \ldots\ldots (1)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad \ldots\ldots (2)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad \ldots\ldots (3)$$

where TP and TN are the true positive and negative, respectively, while FP and FN are the false positive and negative.

The Support Vector Machine (SVM) algorithm is used to classify the heartbeats. The support vector machine is one approach to supervised learning that takes a training dataset with the annotated target as input and outputs a generalizable model, which can then be used to predict the outcomes of the testing dataset[21]. The support vector machine can use kernel functions for linear and non-linear data classification.

The Matlab bioinformatics toolbox provides the statistical techniques needed to apply various tasks efficiently in this work. The training data set and target matrices are needed in the first step to get a generalizable model for classifying the heartbeats later in the testing step. The training matrix's columns consist of features extracted from the heartbeat using ECG segmentation, feature generation, and reduction stages. The target matrix is generated according to the heartbeat in

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the ECG database. The target vectors are generated by putting '1' for heartbeats in the same type of arrhythmia cardiac wanted to be evaluated and putting '-1' for the other heartbeats; the target vector size is equal to the training dataset.

Several experiments are applied to measure the performance of the SVM classifier by using four kernel functions in each experiment (quadratic, polynomial, RBF, and multilayer Perceptron kernel) to get the best SVM classifier results.

4. EXPERIMENTAL RESULTS

There are numerous well-known electrocardiogram datasets for evaluating the computerized interpretation of the ECG signal. The reasons beyond utilizing MIT–BIH arrhythmia dataset [22] are as stated below:

TABLE II THE DIAGNOSIS PERFORMANCE OF LINEAR SVM

Beat type	Training Number	Testing Number	Sensitivity	Specificity	Accuracy
Normal	500	2000	40	79	59.5
LBBB	100	1000	68	94	81
RBBB	100	1000	79	92	85.5
PVC	100	1000	84	78	81
Paced beat	100	1000	92	95	93.5

TABLE III. THE DIAGNOSIS PERFORMANCE OF QUADRATIC KERNEL FUNCTION

Beat type	Training Number	Testing Number	Sensitivity	Specificity	Accuracy
Normal	500	2000	90	84	87
LBBB	100	1000	89	96	92.5
RBBB	100	1000	92	99	95.5
PVC	100	1000	84	93	88.5
Paced beat	100	1000	93	99.5	96.25

TABLE IV. THE DIAGNOSIS PERFORMANCE OF POLYNOMIAL KERNEL FUNCTION.

Beat type	Training Number	Testing Number	Sensitivity	Specificity	Accuracy
Normal	500	2000	96	94	95
LBBB	100	1000	97	98	97.5
RBBB	100	1000	98	96	97
PVC	100	1000	94	95	94.5
Paced beat	100	1000	99	99	99

TABLE V THE DIAGNOSIS PERFORMANCE OF THE GAUSSIAN RADIAL KERNEL FUNCTION

Beat type	Training Number	Testing Number	Sensitivity	Specificity	Accuracy
Normal	500	2000	78.5	89	83.75
LBBB	100	1000	75	98	86.5
RBBB	100	1000	59.7	97	78.35
PVC	100	1000	38	93	65.5
Paced beat	100	1000	42	94	68

TABLE VI. THE DIAGNOSIS PERFORMANCE OF MULTILAYER PERCEPTRON KERNEL FUNCTION

Beat type	Training Number	Testing Number	Sensitivity	Specificity	Accuracy
Normal	500	2000	70	68	69
LBBB	100	1000	37	51	44
RBBB	100	1000	55	65	60
PVC	100	1000	56	68	62
Paced beat	100	1000	86	77	81.5

1. The MIT-BIH Arrhythmia Dataset includes data of healthy electrocardiogram signals as well as data of electrocardiogram signals impacted by non-stationary effects, premature ventricular complexes, left and right bundle blocks, low signal-to-noise ratio (SNR), premature atrial complexes, and finally premature atrial complexes.
2. The MIT-BIH Dataset includes half-hour records for every patient, which is significantly longer than the recordings in several other datasets, for example, the Common Standards for Electrocardiography (CSE) dataset, which has ten-second recordings.
3. This database contains 48 records of Modified Limb Lead II (MLII), lead v1, v2, v4, and v5. These records were taken randomly from more than 4,000 twenty-four hour monitored tapes; the records are an ECG signal for 30 minutes sampled at 360 Hz with an average of 2000 beats; also, each beat type is tagged with about 18 ECG beat types.

This system is evaluated by training and testing dataset of modified limb lead II (MLII), which means 46 records are only used, and the training and testing dataset is chosen randomly from the database. The performance of this system is illustrated in Tables II, III, IV, V, and VI. The SVM classifier of the Polynomial kernel (Table IV) is the best one because it gives high sensitivity and specificity as compared with other kernel functions.

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5. CONCLUSION

ECG is a vital instrument in the healthcare system; an automated ECG analysis is useful in assisting the medical crew and remote monitoring. In this research, an automated ECG diagnosis is designed and implemented on the MIT-BIH dataset. The use of wavelet transforms for the ECG signal in the diagnosis gave a closer look at the frequency contents and the locations of the disturbances, which are essential for the diagnosis. The use of Duabechies6 (DB6) as a mother wavelet gave a suitable decomposition for the ECG to its components because of the shape similarity, which is usually preferred in such cases. Using the PCA algorithm helped reduce the number of features from 300 to 20, but without the same order of a loss of information, this made the training and diagnosis easier and faster. SVM classifier of polynomial kernel function made the system more robust and improved the system's accuracy compared to other kernel functions. For future work, more arrhythmia types are needed to be diagnosed and modify the design to work in real-time; and the accuracy can be enhanced by using a larger dataset; also, deep learning machine techniques can be used.

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