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Using the Electrocardiogram Signal to Identify and Detection Heart Diseases by Combining Time and Frequency Characteristics

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Abstract
One highly valuable tool for diagnosing heart diseases is the Electrocardiogram (ECG). This method involves recording the electrical signals emitted by the heart, using electrodes placed on the chest and various organs. The primary objective of this project is to employ digital signal processing of ECG signals to classify and diagnose heart diseases. The conditions that can be classified through this digital processing of ECG signals encompass arrhythmia, atrioventricular block, cardiomyopathy, bundle branch block, and more. Therefore, this study primarily focuses on the classification and diagnosis of some of these heart diseases. The Pan-Tompkins algorithm is employed in this study to detect the QRS complex in the ECG signals. Various classification algorithms, such as K-Nearest Neighbor, support vector machine, decision tree, and neural network, have been utilized to classify these signals. The digital processing of ECG signals is conducted using the MATLAB software. The ECG signals utilized in this project were sourced from the PTB Diagnostic database available at physionet.org. Ultimately, the K-NN classifier with an F-criterion of 0.88 and a K-value of 20 demonstrated the most robust performance in classifying these heart diseases.

Keywords: Electrocardiogram, Heart Disease Classification, K-Nearest Neighbor, Support Vector Machine, Neural Network.

1. INTRODUCTION

Based on data from the World Health Organization, heart disease ranks as the second leading cause of human mortality,

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resulting in a significant number of fatalities [1,2].

Consequently, any advancements in the treatment and diagnostic tools for this condition would greatly benefit society and garner increased attention within the medical field [3,4].

Numerous diagnostic tools are available for the evaluation and treatment of heart disease. Diagnostic tests include the exercise stress test (EST) [5,6], treadmill test [7,8], electrocardiogram (ECG) [9,10], echocardiogram [11,12], and cardiac catheterization [13]. In the case of coronary artery disease diagnosis, a standard ECG employing physiological systems is typically employed. However, accurately identifying subtle changes in ECG signals can be challenging [14,15]. Computer-aided diagnostic tools have emerged to enhance the precision of heart health diagnoses by detecting subtle alterations in electrocardiogram signals [16,17]. ECG signals play a pivotal role in monitoring much of the heart's function, providing a clear graphical representation of each part's performance [18,19]. These ECG signals are typically recorded on gridded paper, with time represented on the horizontal axis and voltage on the vertical axis [20,21].

There are several ways in which we can identify and classify ECG signals [22,23]. Most of the methods used for detection are Pan-Tompkins's method, wavelet transform, etc. For signal classification, there are algorithms such as K-Nearest Neighbor, probabilistic neural network, support vector machine, artificial neural network, fuzzy logic system, and many other methods [24,25]. This study aims to diagnose heart diseases from ECG signals with digital signal processing. After identifying the diseases, a proper diagnosis is given. Therefore, this method will be of great help to patients as well as physicians, because this method is done automatically and only an initial check by the doctor is enough. Various cardiovascular diseases can be diagnosed and classified using ECG signals. The pre-recorded ECG signals used in this research were obtained from physionet.org to identify and diagnose 4 heart diseases as follows [26,27]:

1. Myocardial infarction: A heart attack, which is also called a myocardial infarction or MI, occurs when the blood flow in a part of the heart is reduced or stopped, causing damage to the heart muscle. The most common symptom is pain or discomfort in the chest area, and it may shoot in the shoulder, arm, back, neck, or jaw.

2. Cardiomyopathy: Heart muscle disease or cardiomyopathy is a different group of heart muscle diseases, as a result of which the heart cannot provide enough blood flow to the body parts, and the person suffers from heart failure, which is often associated with arrhythmia.

3. Bundle branch block: Heart block is one of the types of cardiac arrhythmia (meaning abnormal heart rhythm). The normal rhythm of the heart starts from the sinus node and spreads in the ventricles after being transferred to the atria-ventricular node. As a result of this way of conducting electrical stimulation, first the atrium and after a short distance the ventricles contract. The normal rhythm of the heart is between sixty and one hundred beats per minute. The wave of electrical stimulation of the heart may slow

or stop at some point in the path, which is called a heart block. Heart block can be complete or branchial.

4. Dysrhythmia: Arrhythmia, also known as cardiac arrhythmia or dysrhythmia, is an irregular heartbeat, including when it beats too fast or too slow. A resting heart rate that is too fast- above 100 beats per minute in adults- is called tachycardia, and a resting heart rate that is too slow - below 60 beats per minute - is called bradycardia. Some types of arrhythmias have no symptoms. Symptoms, if present, may include palpitations or a feeling of pauses between heartbeats.

2. PROPOSED ALGORITHM

This study aims to classify four specific heart diseases and facilitate their diagnosis. The current focus is on a limited set of diseases, but the project has the potential to expand its scope to identify and classify a broader range of heart conditions. Such classifications can serve as valuable reference tools for health-care professionals. Diseases are categorized separately when all relevant details are available, while those lacking comprehensive information are grouped with diseases exhibiting similar ECG signal patterns.

2.1. Database Generation

This study primarily focuses on diagnosing detectable heart diseases through the analysis of ECG signals. To achieve this objective, we have chosen the "ECG diagnostic PTB database" provided by the German National Institute of Metrology. This database offers a comprehensive collection of digitized ECGs, making it accessible to researchers, benchmarking algorithm development, and training purposes. The database comprises 549 cases obtained from 290 patients with ages ranging from 17 to 87 years. Each case includes 15 simultaneously measured signals. Furthermore, the database also includes a summary file containing the patient's clinical information, such as age, gender, diagnosis, ventriculography, echocardiography, and hemodynamics.

2.2. Preprocessing

Preprocessing plays a crucial role in the primary processing of ECG signals. Its purpose is to eliminate any abnormalities and noise present in the ECG signals, as failing to do so can adversely impact the clinical information used for interpretation [28]. To achieve this, a variety of filters are employed during the preprocessing of ECG signals. These filters effectively eliminate undesired anomalies, allowing the extraction of the pertinent features from the signal of interest [29,30]. Given that these signals are obtained from an open database, they may contain noise, power line interference, and irregularities. Consequently, signal preprocessing is indispensable, and for this purpose, fundamental filters are employed to effectively eliminate noise and anomalies.

2.3. Pan Tompkins Algorithm

In this study, we will employ the Pan-Tompkins algorithm to identify the QRS complex (Fig. 1). This algorithm aids in the detection of the QRS complex by analyzing various characteristics of the electrocardiogram signal, such as amplitude, slope, and more [31,32]. To detect the QRS complex using the Pan-Tompkins algorithm, the signal undergoes a sequence of stages, including passage through the discriminator filter, the squaring operator, and the integration phase. Information is processed through the integration phase before determining the threshold, ultimately leading to the detection of the QRS complex. The inclusion of a band-pass filter serves the purpose of mitigating various types of interference in the signal, such as muscle noise, power line interference, and baseline interference [33,34].

2.4. Classification

A. Utilizing K-Nearest Neighbors for Classification

The K-Nearest Neighbors (KNN) algorithm is a supervised machine learning technique applicable to both classification and predictive regression tasks. In practice, it finds prominent use in predictive classification problems within various industries. KNN leverages the concept of "feature similarity" to make predictions for new data points, essentially assigning a value to the new data point based on its resemblance to the existing points in the training dataset [35,36].

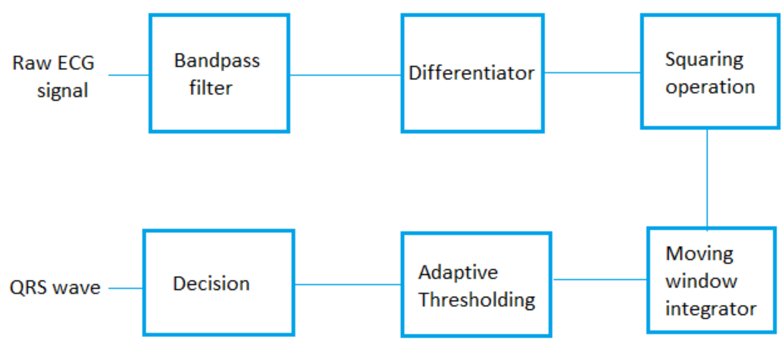


Fig.1 Steps for pan Tompkins algorithm.

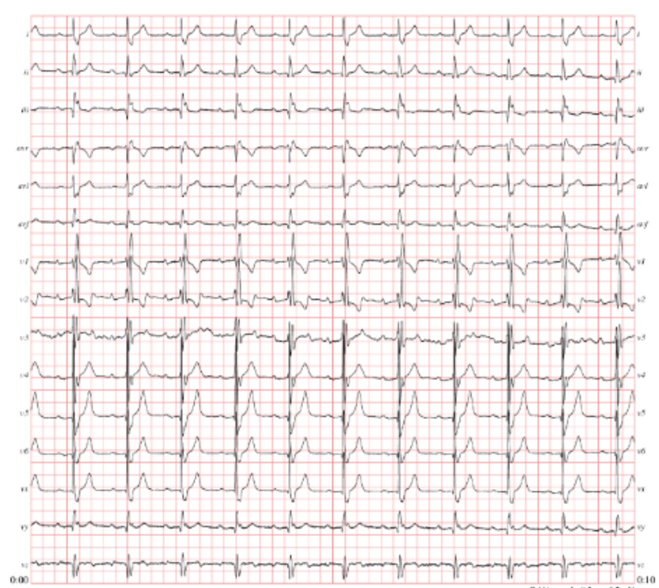
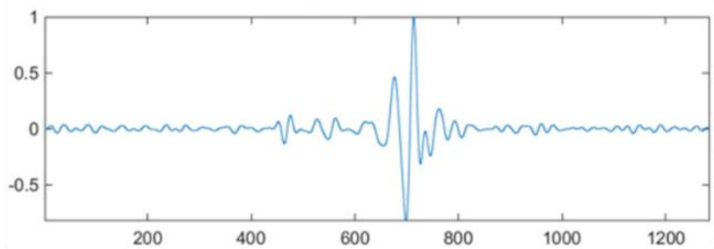


Fig.2 Raw ECG signal of myocardial infarction.



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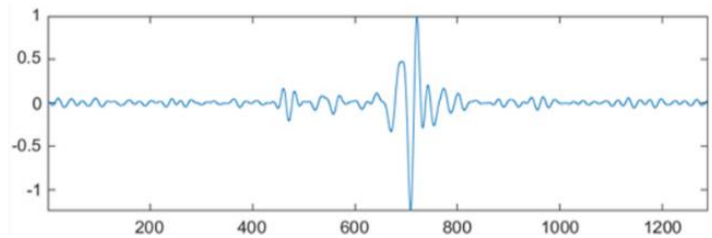

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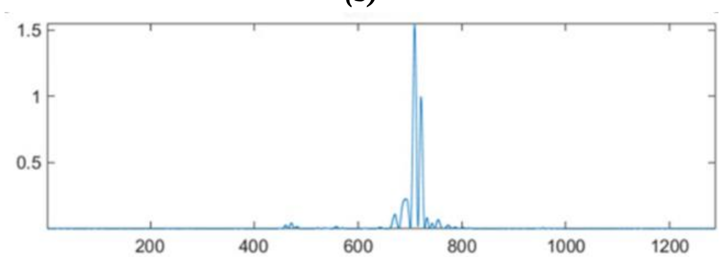

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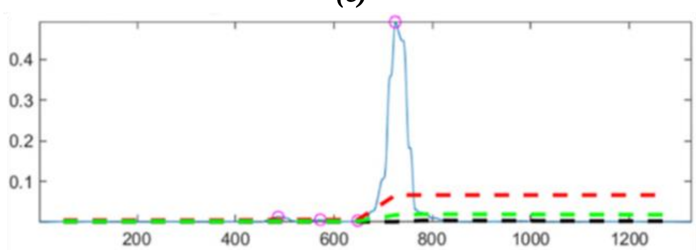


(d)

Fig.3 Output of Pan-Tompkins's algorithm for the case of myocardial infarction. a) Band-pass filter output. b) Derivative filter output. c) Squared filter output. d) Averaged with 30 sample lengths, Black: noise, Green: Adaptive Threshold, Red: Sig Level, Circles: QRS Adaptive Threshold.

B. Classification Using Decision Tree

A decision tree is a method for classifying data by dividing it into smaller segments through a series of tests defined at each node. Typically, decision trees consist of a primary node (the root), intermediary nodes, and terminal nodes (the leaves). The process begins at the root node, where the tree branches into left and right branches, each representing a specific range of values. This iterative process continues, guided by the least squares error criterion until the estimation error of the dependent variable is minimized. In a decision tree, each node has a single parent and two or more children. One notable characteristic of decision tree algorithms is their straightforward interpretability, utilizing a hierarchical tree structure. Unlike many other machine learning methods, decision tree algorithms are often described as "white-box" methods because they facilitate a clearer understanding of the relationship between input and output variables [37].

C. Classification by Neural Network

Neural networks draw inspiration from the emulation of human brain behavior, with their learning capability standing out as a crucial attribute. These networks excel due to their adaptability and robust learning prowess, not only learning from historical data but also enhancing their performance during the learning process. Acting as computational models, neural networks proficiently discern the connection between input and output within a physical system through an intricate web of interconnected nodes. The growth and refinement of a neural network model necessitates attention to the design of its technical components. A neural network comprises fundamental processing elements known as neurons, organized into distinct layers. Typically, these layers include three key categories input, hidden, and output layers, although networks can incorporate multiple hidden layers. The construction of such neural network models requires access to training, validation, and test datasets. Training data facilitates the discovery of relationships between observed inputs and corresponding outputs, validation data acts as a check to ensure the network's learning accuracy, and test data is employed to evaluate the performance of the proposed network [38].

D. Classification by Support Vector Machine

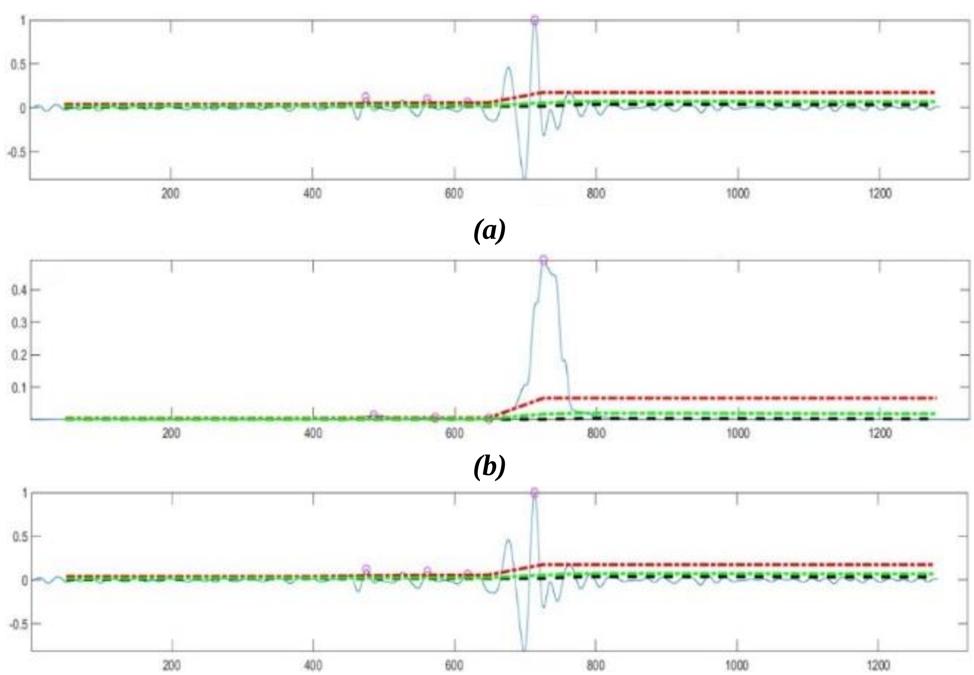
The Support Vector Machine (SVM) stands out as a prominent classifier within the domain of kernel-based methods in machine learning. Widely acknowledged, the SVM algorithm holds a significant position in supervised learning, effectively serving both classification and regression tasks. Renowned for its distinctive ability to simultaneously maximize geometric margins and minimize experimental classification errors, SVM is often referred to as "maximum margin classification." In binary classification scenarios, where there are two outcome categories, several lines can be drawn for classification. However, only one of these lines achieves maximum separation. Amidst various linear separators, the one that maximizes the margin within the training data is the most effective in minimizing generalization errors. While multiple linear classifiers may meet this requirement, SVM aims to identify the classifier that optimally separates classes, ensuring robust classification [39].

3. SIMULATION RESULTS

The database includes 549 records derived from 290 cases, spanning ages 17 to 87 years, with an average age of 57.2 years. Within this dataset, 209 cases belong to men, averaging 55.5 years, and 81 cases to women, averaging 61.6 years. Age information is unavailable for one woman and 14 men. Each case is represented by one to five records, with records numbered 124, 132, 134, and 161 being absent. Each record comprises 15 simultaneous measurement signals, encompassing 12 standard signals (i, ii, iii, avr, avl, avf, v1, v2, v3, v4, v5, v6), along with Frank's 3-lead ECG signals (vx, vy, vs). These signals are recorded at a rate of 1000 samples per second, featuring a 16-bit resolution within the ±16.384 mV range. Additionally, in accordance with contributors' requests, the database provides records that can be made available at various sampling rates, potentially reaching up to 10 kHz.

3.1. Myocardial Infarction Test

Like other muscles in the human body, the heart relies on a constant supply of oxygen and nutrients for its proper functioning. Oxygen-rich blood is delivered to the heart muscle through a network of branching arteries. When a blockage occurs in one of the coronary arteries or its branches, it disrupts the flow of oxygen to a specific region of the heart, leading to a condition known as "cardiac ischemia." In cases of prolonged cardiac ischemia, where a portion of the heart tissue remains deprived of oxygen, that affected tissue can become necrotic. This serious complication is commonly referred to as a "heart attack" and medically known as a "myocardial infarction," which translates to the "death of heart muscle". To diagnose a myocardial infarction, various tests are available, including blood tests, electrocardiograms (ECG), and coronary angiography. An ECG, which records the heart's electrical activity, can help confirm a specific type of heart attack known as ST-elevation myocardial infarction (STEMI) by identifying changes in the elevation of the ST segment.



(a)

(b)

(c)

Fig. 4 a) QRS on Filtered signal. b) QRS on MVI signal and Noise level (Black), Signal level (Red), and Adaptive Threshold (Green). c) pulse train of the founded QRS in ECG signal related to myocardial infarction case.

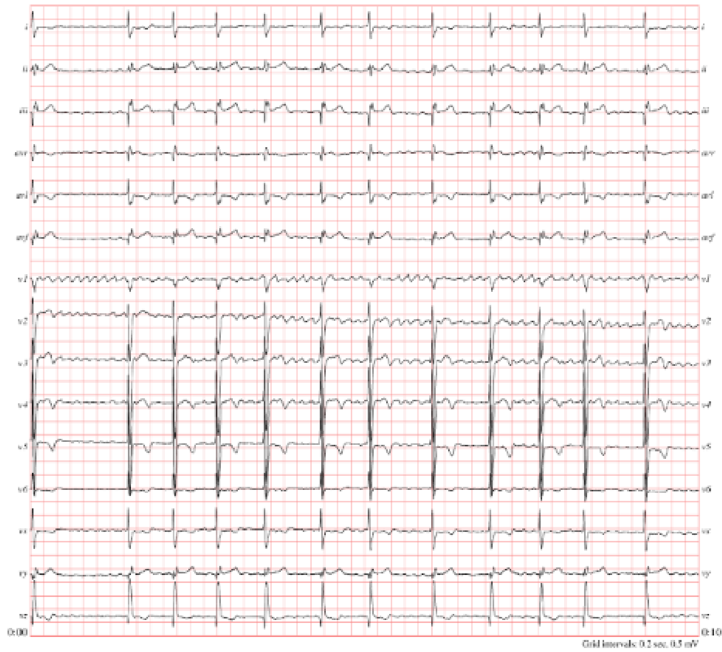


Fig.5 Raw ECG signal of cardiomyopathy.

Time is of the essence in treating myocardial infarctions. For individuals suspected of having a heart attack, the immediate and most appropriate treatment involves the administration of aspirin tablets. In cases of low oxygen levels or breathing difficulties, supplemental oxygen should be administered. Chest pain is the predominant symptom observed in cases of acute myocardial infarction.

3.2. Cardiomyopathy test

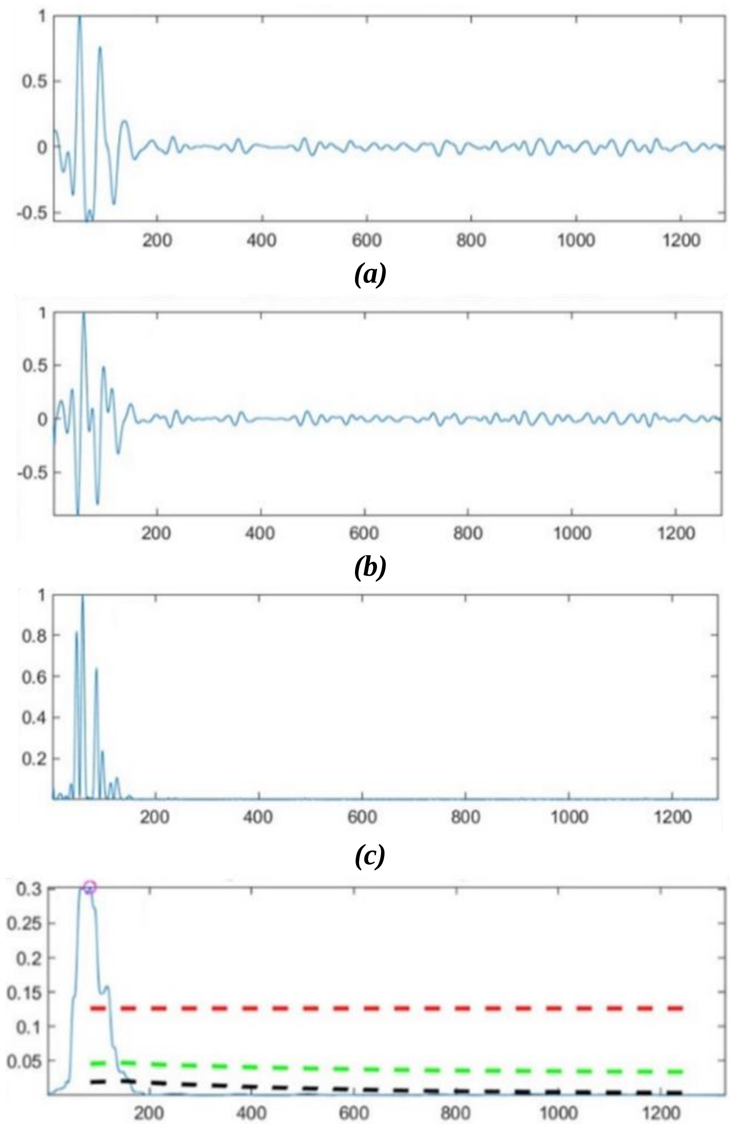
This disease is completely related to the heart muscle. When this disease occurs, it shows many signs and symptoms. In this disease, a large and thick heart muscle can be seen. In some cases, the heart muscle tissue must be replaced with scar tissue. The ventricles are enlarged and weakened in dilated cardiomyopathy. In the worst stage of cardiomyopathy, the heart becomes very weak. The ability to pump blood in the body decreases and it is difficult to maintain a normal electrical rhythm. This may sometimes lead to heart failure or some arrhythmias in which the heart beats irregularly. This heart failure may also lead to fluid accumulation in some major parts of the body such as the lungs, abdomen, etc. It also shows heart valve problems due to its weakening. Cardiomyopathy is divided into two types including acquired and hereditary.

The acquired condition of this disease is for people who are not born with this disease but are caught by it during their lives. If the gene for this condition is passed from parents to children, they will be affected by this disease.

Most of the time, the cause of cardiomyopathy is unknown. This disease occurs in people of different ages. However, different types of cardiomyopathies are observed in different age groups [40].

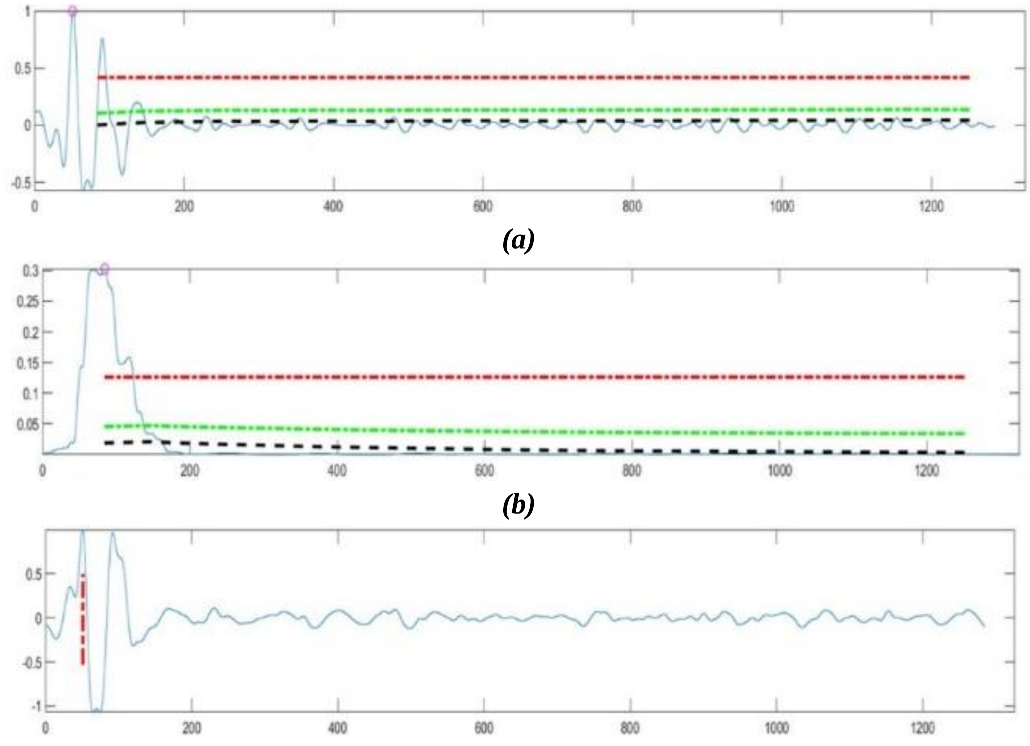
3.3. Bundle branch block test

A bundle branch block occurs when there is a delay or blockage in the path where electrical impulses travel to make the heartbeat. A blockage or delay may occur in the way electrical impulses are sent to the left or right side of the lower chambers (ventricles) of the heart. Branch block makes it harder for the heart to pump blood through the circulatory system. There is no complete cure for this condition alone, but any condition that causes bundle branch block should be treated before it develops. This disease does not cause any symptoms in most people, and they do not even know that they have this condition. In some people, symptoms such as fainting and fainting are observed.



(d)

Fig. 6. Output of Pan-Tompkins's algorithm for the case of cardiomyopathy. a) Band-pass filter output. b) Derivative filter output. c) Squared filter output. d) Averaged with 30 sample lengths, Black: noise, Green: Adaptive Threshold, Red: Sig Level, Circles: QRS Adaptive Threshold.



(a)

(b)

(c)

Fig.7. A) QRS on a Filtered signal. B) QRS on MVI signal and Noise level (Black), Signal level (Red), and Adaptive Threshold (Green). C) pulse train of the founded QRS in ECG signal-related cardiomyopathy case.

Fig.8 Raw ECG signal of bundle branch block.

There are two types of batch branch blocks including the right and left batch branch block. Any problem on the right side of the heart is indicated by the abbreviation RBBB. A person is considered healthy when the QRS complex with normal duration is in RBBB. LBBB is considered a symptom of heart disease mostly related to the left ventricle. The atrial septal defect should first be suspected when RBBB is diagnosed. Ischemic disease and aortic stenosis should be considered whenever LBBB is diagnosed. No action is required if the patient is asymptomatic. If the patient is suffering from chest pain, LBBB indicates an acute myocardial infarction [41.42].

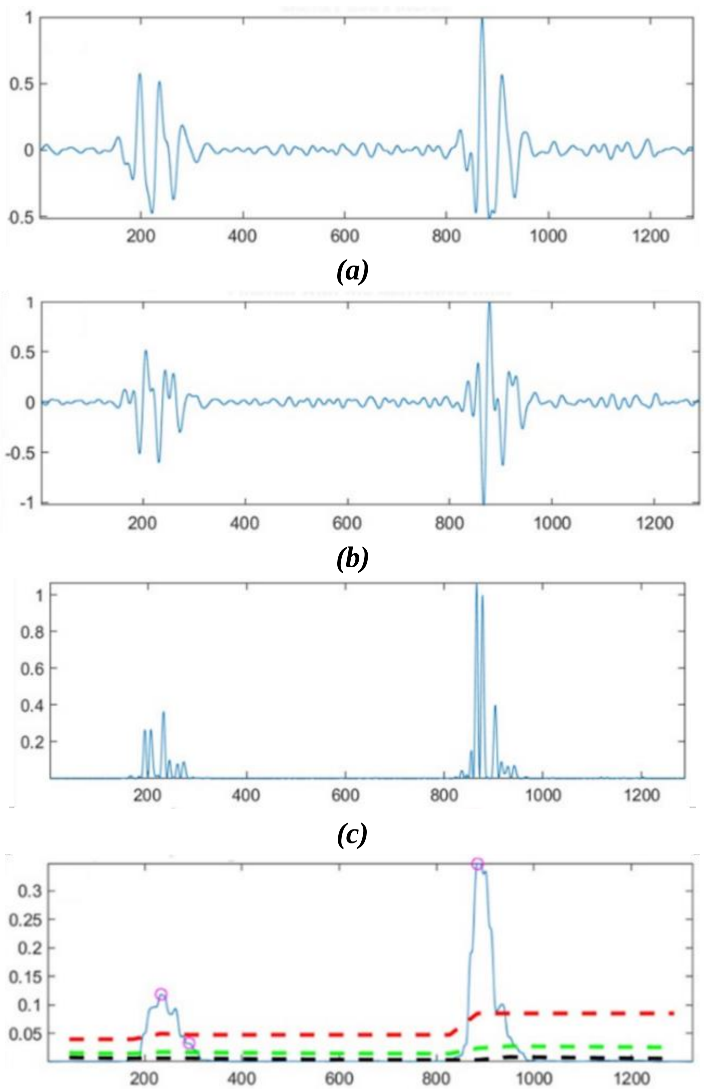
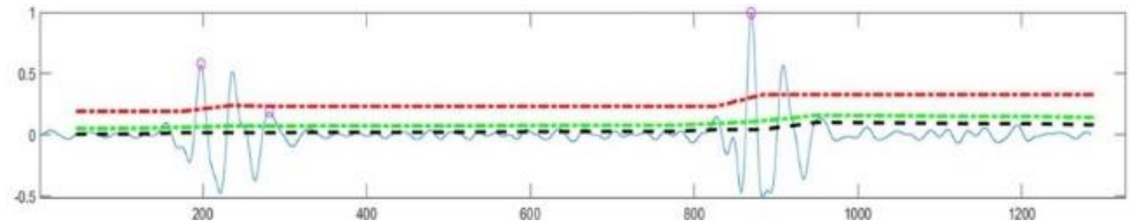
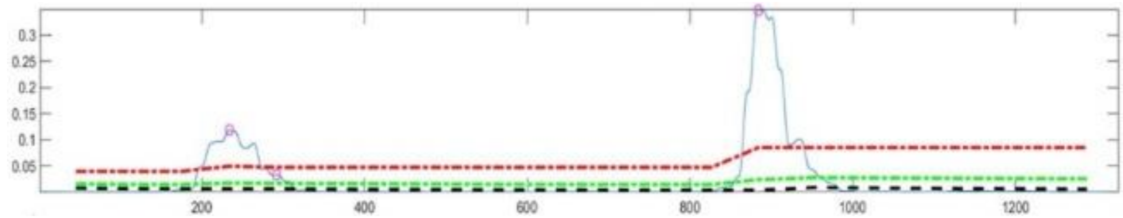


Fig.9 Output of the Pan-Tompkins algorithm for the bundle branch block case. a) Bandpass filter output. b) Derivative filter output. c) Squared filter output. d) Averaged with 30 sample lengths, Black: noise, Green: Adaptive Threshold, Red: Sig Level, Circles: QRS Adaptive Threshold.



(a)



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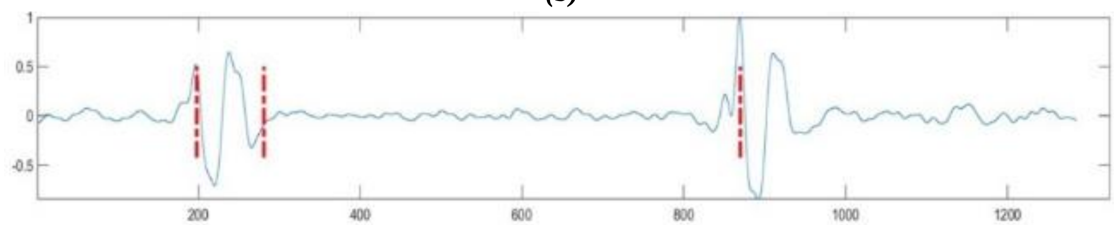


(c)

Fig.10 a) QRS on Filtered signal. b) QRS on MVI signal and Noise level (Black), Signal level (Red), and Adaptive Threshold (Green). c) pulse train of the founded QRS in ECG signal-related bundle branch block case.

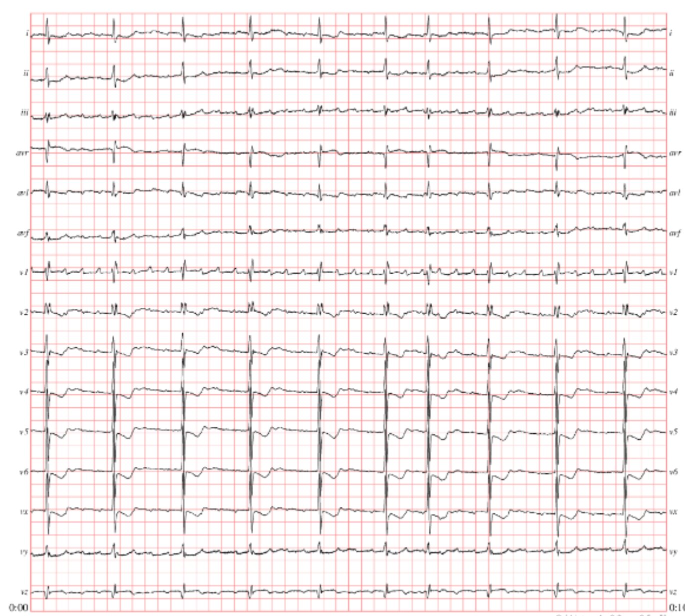
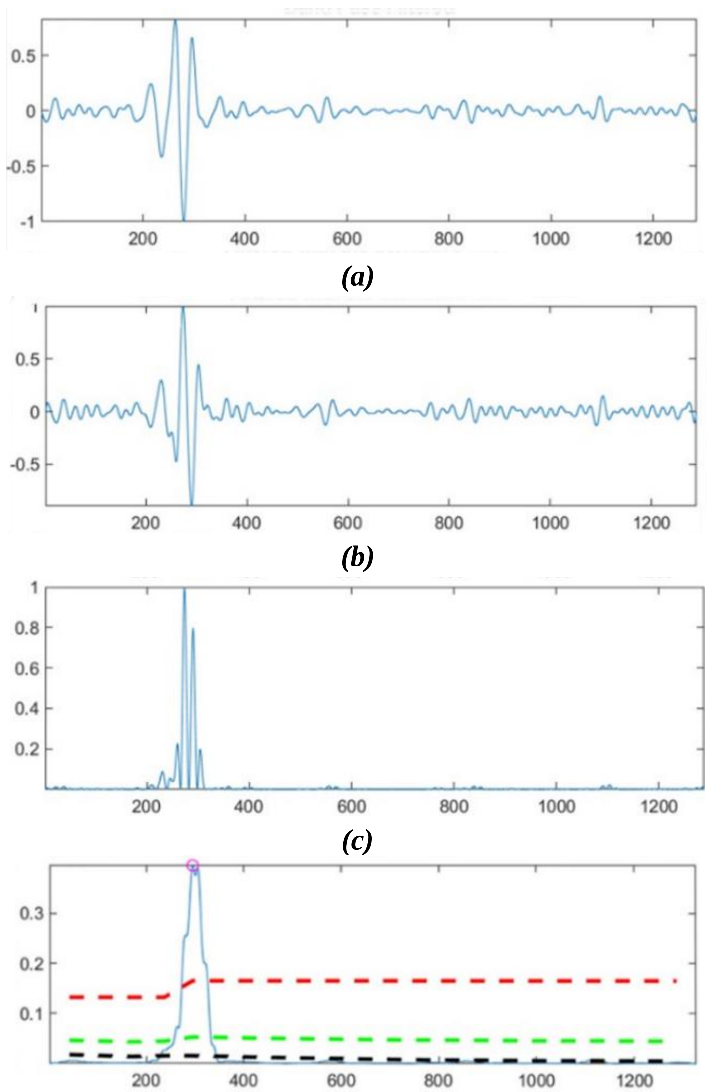


Fig.11 Raw ECG signal of dysrhythmia.

3.4. Dysrhythmia test

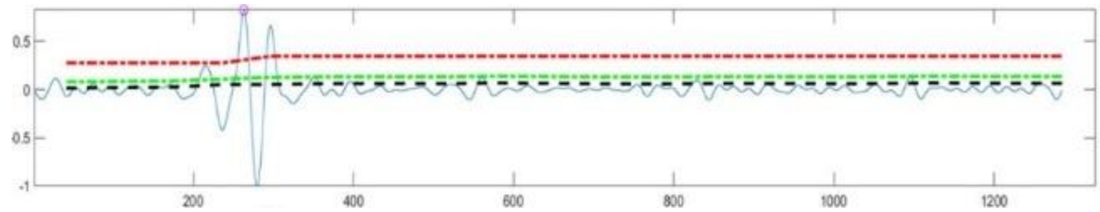
An abnormal heartbeat is considered a cardiac dysrhythmia. In this case, the heart rate is irregular, or the heart rate may be low or high. Some types of dysrhythmias are considered potentially life-threatening, while others are considered normal (such as sinus arrhythmia).

There are several types of dysrhythmias, classified by origin (atrial and ventricular) and heart rate. If the heart rate is higher than normal (more than 100 beats per minute), it is considered tachycardia. Tachycardia can originate from the atria or ventricles.



(a) ***(b)*** ***(c)*** ***(d)***

Fig.12 Pan-Tompkins's algorithm output for dysrhythmia case. a) Band-pass filter output. b) Derivative filter output. c) Squared filter output. d) Averaged with 30 sample lengths, Black: noise, Green: Adaptive Threshold, Red: Sig Level, Circles: QRS Adaptive Threshold.



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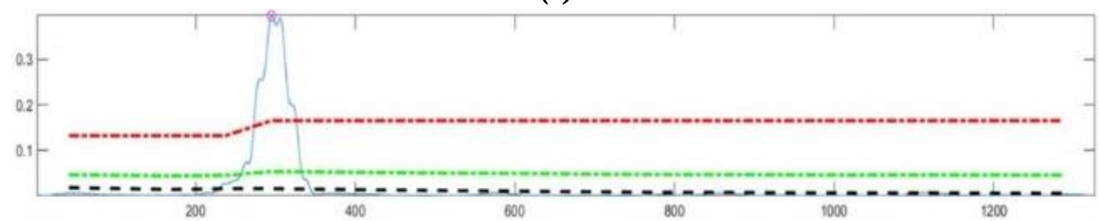

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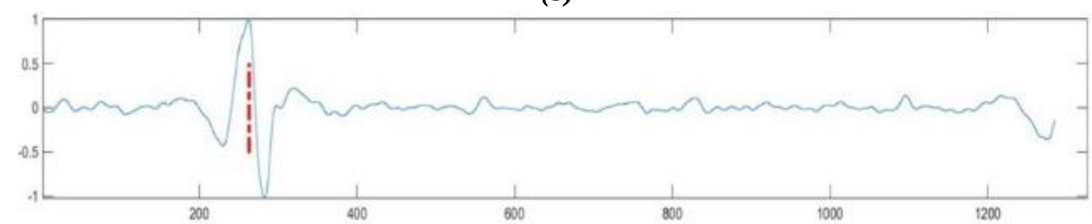


(c)

Fig.13 a) QRS on Filtered signal. b) QRS on MVI signal and Noise level (Black), Signal level (Red), and Adaptive Threshold (Green). c) pulse train of the founded QRS in ECG signal related to dysrhythmia case.

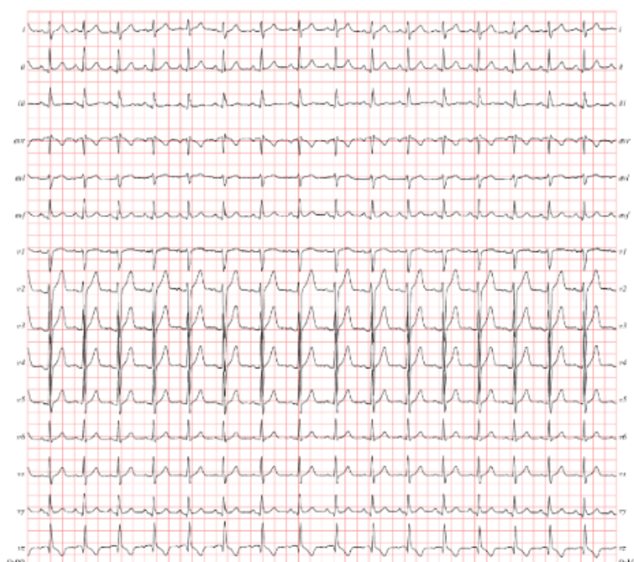


Fig.14 Raw ECG signal of a healthy person.

Complications originating from the atria are called supraventricular dysrhythmias and include:

1. Atrial fibrillation
2. Atrial flutter
3. Wolff-Parkinson-White syndrome

4. Sudden supraventricular tachycardia

Complications that originate in the ventricles are called ventricular dysrhythmias and include:

1. Premature ventricular contractions
2. Ventricular fibrillation
3. Long QT syndrome

If the heart rate is lower than normal (below 60 beats per minute), it is considered bradycardia. There are various methods to test for dysrhythmia, such as Holter monitor, EKG, stress test, event monitor, cardiac catheterization, etc.

3.5. Healthy Control test

An ECG tape that does not show any abnormalities is considered healthy. Some of the physical characteristics of these healthy signals are as follows:

P wave: completely vertical in leads I, aVF, and V3-V6. The duration of this wave is less than or equal to 0.11 seconds. It should not have peaks or notches and should be generally smooth.

PR interval: The duration of this wave should be between 0.12 and 0.20 seconds.

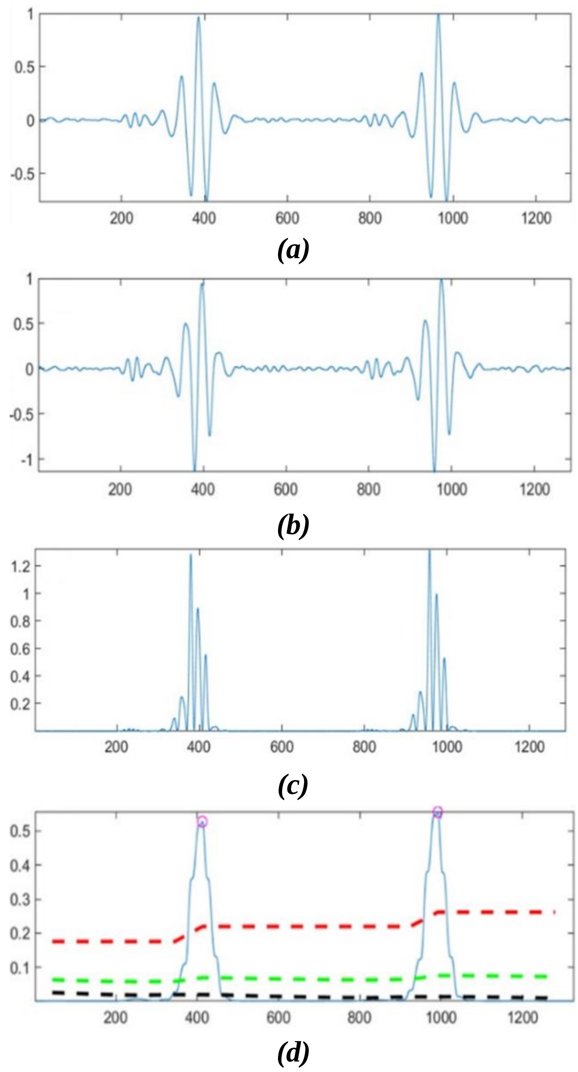
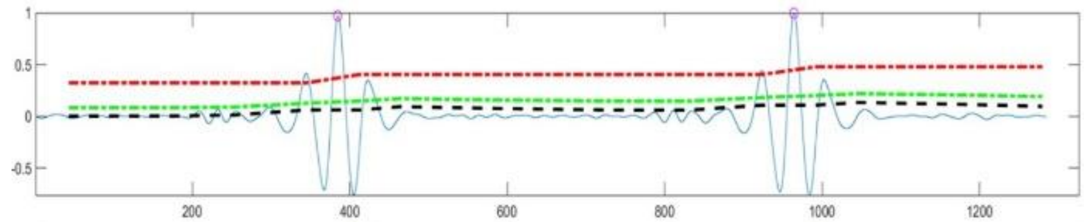


Fig.15 Output of Pan-Tompkins algorithm for the case of a healthy person. a) Bandpass filter output. b) Derivative filter output. c) Squared filter output. d) Averaged with 30 sample lengths, Black: noise, Green: Adaptive Threshold, Red: Sig Level, Circles: QRS Adaptive Threshold.



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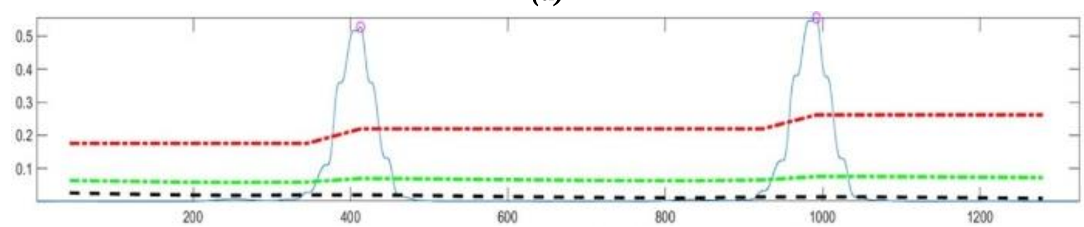

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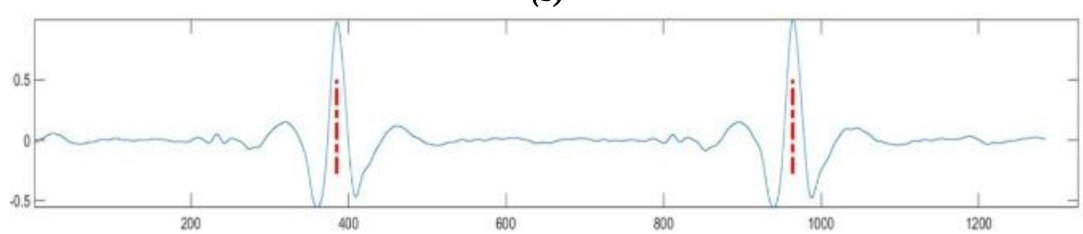

(c)

Fig.16. a) QRS on a Filtered signal. b) QRS on MVI signal and Noise level (Black), signal level (Red), and adaptive threshold (Green). c) pulse train of the founded QRS in ECG signal related to the healthy case.

QRS complex: its duration is less than 0.12 seconds; its amplitude must be greater than 0.5 mV in at least one standard lead. At least one precordial (cardiac) lead should have an amplitude greater than 1.0 mV. Generally, one should move from leads V1 to V6, along the way the R waves get taller while the S waves get smaller. In lead V3 or V4, the S and R waves are equal. This area is also called the transition area.

ST region: On a normal ECG, this region should be isoelectric and have an upward-sloping T wave. There should not be more than 0.5 mm of depression in any lead.

T wave: The deviation of this wave must be in the direction of the QRS complex for at least 5 of the 6 organ leads. In leads V2 to V6 this wave should be vertical and inverted in lead aVR. In leads V3 and V4, its range should be at least 0.2 mV, and in leads V5 and V6 at least 0.1 mV.

QT zone: The interval of this zone should be less than 0.40 seconds for men and 0.44 seconds for women [43].

4. Evaluation criteria

There is an important parameter called "F-Measure", which is widely used to evaluate the performance of categories and is obtained from the combination of two parameters, Positive Prediction Value, and Negative Predictive Values. With the explanation that the parameter of positive predictive value is called Precision, and Negative Predictive Values is called recall, "F-Measure", "Precision" and " recall", are defined as follows [44,45]:

$$PPV = \frac{TP}{TP + FP} \quad (1)$$

$$NPV = \frac{TN}{TN + FN} \quad (2)$$

$$F - Measure = \frac{2(Recall)(Precision)}{(Recall + Precision)} \quad (3)$$

The confusion matrix was obtained when the value of k=[1,10,20] and K-NN classifier and

Table 1. ***Confusion matrix obtained when the value of k=1 and K-NN classifier.***

True case	Case prediction				
	1	2	3	4	5
1	112	4	2	3	8
2	9	12	0	0	5
3	6	1	11	0	3
4	4	0	0	10	1
5	17	1	2	1	35

Table 2. ***Confusion matrix obtained when the value of k=10.***

True case	Case prediction				
	1	2	3	4	5
1	122	3	2	2	6
2	7	13	0	0	3
3	3	1	12	0	2
4	2	0	0	11	0
5	14	2	1	1	41

F-measure obtained [0.63,0.75,0.88] respectively (see Table 1, 2 and 3). In the same way, the F-measure for the other classifiers is obtained and shown in Table 4.

For the data obtained above, the input is taken as follows:

Case 1 - Myocardial Infarction – 148 signals
Case 2 – Cardiomyopathy – 18 signals
Case 3 – Bundle branch block– 15 signals
Case 4 – Dysrhythmia – 14 signals
Case 5– Healthy signals – 52 signals

Table 3. ***Confusion matrix obtained when the value of k=20.***

True case	Case prediction				
	1	2	3	4	5
1	138	3	1	1	7
2	3	13	0	0	2
3	1	1	13	1	0
4	0	0	0	12	0
5	6	1	1	0	43

Table 4. ***F-measure for the other classifiers.***

F-measure	K		
	1	10	20
K-NN	0.63	0.75	0.88
NN	0.57	0.67	0.77
DT	0.51	0.65	0.76
SVM	0.53	0.63	0.72

5. CONCLUSIONS

With the proposed system, we can classify 5 ECG signals into corresponding diseases (4 disease classes and 1 healthy class). Diseases focused on include cardiomyopathy, myocardial infarction, bundle branch block, dysrhythmias, and healthy signals. The reason for focusing on these 5 signals is the signal database itself. If many types of disease databases are provided, it can be worked on and the existing diseases can be classified. To obtain more complete results, more signals are needed so that each disease can be trained more effectively. In evaluating the performance of the classifiers according to the F-measure, the result showed that the K-NN classifier has the best performance among other classifiers. In addition, the performance of all classifiers increases with the increase of the k value (repetition of training). Finally, the K-NN classifier has the best performance with F- measure=0.88 (for K=20). Only the diseases mentioned in this article can be classified using the database in question, and for any other ECG signal tested in this way, the corresponding algorithm will provide the closest result. As one of the main points, the most accurate results are obtained when there are many signals to train on. Finally, the current research will end with the view that all the mentioned goals have been successfully achieved.

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