Journal of University of Duhok, Vol. 24, No.2 (Pure and Eng. Sciences), Pp 114-123, 2021

AN ECG CLASSIFIER USING FIR WITH A QRS RESPONSE

DINA RIYADH IBRAHIM
Dept. of Communication Engineering, Electronic Engineering, University of Nineveh, Mosul-Iraq

(Received: August 24, 2021; Accepted for Publication: November 28, 2021)

ABSTRACT

Recording the electrocardiography (ECG) signals is one of the main ways to diagnose heart disease cases through detecting the total or partial alterations in the P wave, QRS complex, or T wave of the signal. This bioelectrical signal is used to detect and visualize any irregular changes in the heart's electrical activity. The two fundamental steps for ECG signal analysis are identifying the QRS complex and providing more details on the disease under medical investigation. The discrete-time response of a high-pass FIR filter is achieved by equating the time coefficients of the filter with a discretized version of the QRS complex part of a standard ECG signal. The high-pass FIR filter helps reduce the interference of the 50 Hz power supply. A matched filter is designed using the discrete-time response of the high pass FIR filter, and the resulting matched filter response simulates a complex part of the QRS of an average ECG signal. When an ECG of a patient is applied as an input to the designed matching filter, the best fit correlated output coefficients of the patient ECG are obtained. The filter output coefficients are applied to the artificial neural network (ANN) recognition system to verify and classify the ECG input to four categories which are(AF, CHF, QT, and PTB) . The overall system can operate with an accuracy of 98%.

KEYWORD :Electrocardiography(ECG) , Matched filter , Artificial Neural Network (ANN)

1. INTRODUCTION

ECG signal is an effective means of diagnosing any abnormality in the electrical functioning patterns of the heart. The typical pattern of an ECG signal of the heart usually consists of a P wave, QRS complex, and T wave [1]. The recording of this bioelectrical signal requires connecting the ECG electrodes to specific spots in the human body. One significant problem of converting the analog ECG into the digital format is the noise interface caused by many factors such as the breathing muscle artifact and the 50Hz frequency power supply network. Due to the considerable influences of noise reduction on the efficiency of the ECG processing system, the analysis of the denoised ECG signal is usually accomplished by the initial process of filtering the 50Hz power line using the LMS notch filter. It is essential to remove the 50Hz noise from the ECG signal to be used in the next stage of the processing system, which is designed to enhance the QRS complex by extracting the noise-free frequency ranges of ECG signals [2]. As a bioelectrical signal, the ECG signal registers the heart's electrical activity and identifies any potential irregularities caused by slow or fast heartbeat. The signal, measured using electrodes and plotted in the form of electrical activity [3], consists of several wave parts; P wave, QRS complex, and T wave [4]. These waves are considered crucial factors in ECG signal analysis, and they provide more details that assist the disease diagnosis [5].

2. LITERATURE REVIEW

Many signal processing systems can detect different types of heart disease based on ECG signals. Other parts of the PQRST signal may affect the detection and classification of heart disease [6]. In 2012, a QRS complex-detection method was presented based on the multi-resolution wavelet transform PQRST peak points are stored and marked over the time interval between the first (R) and other peaks used to detect anomalies in the heart physiological functionality through thresholding. The accuracy of the P-QRS-T complex interval detection went high up to a high exactitude of 100%. The signal processing system presented in that method leads to the detection and identification of many heart diseases based on the shape of the ECG signal[6]. Also, in 2012, the 1st derivative of a Gaussian function was

dina.ibrahim@uoninevah.edu.iq

adopted as a mother wavelet function to design the decomposition filter bank. The magnitudes of the intervals and resulting amplitudes in this method were compared with a valid ground to diagnose a set of human heart diseases. The accuracy of (PQRST) complex interval and detection measurement may reach 100% with a high exactitude. Convolution-based linear filtering is usually used for QRS detection to suggest a new method using the convolution of sequence. These two algorithms are used in the preprocessing of ECG signals [7], [8].

In 2013, two consecutive pre-processing steps (wavelet transform and linear filtering) were applied to the input ECG signal for the QRS detection via the convolution method of sequences [9]. In the processing stage of analyzing ECG algorithms, the convolution operators were used to create the coefficients for the ECG signal. A QRS complex-like FIR filter bank response was designed in the same year using the first derivative of Gaussian function with a standard derivation of 4.5 [10]. The designed FIR filter bank was made in a lattice structure to decompose the input ECG signal. The energies of various filter bank output coefficients were calculated and used as a critical point in simulating disease correspondences in the tested ECG signal. A rule-based fuzzy identification system was introduced, resulting in 100% accuracy for the five tested disease cases[10].Wavelet transform was applied to ECG signals to detect diseases such as ischemia, and the algorithm used in this method reflected an excellent capability for learning and detection [11]. The medical heart conditions diagnosed from ECG signals were classified into two main categories: normal and abnormal. The noticeable abnormality was categorized into several groups such as RBBB, LBBB, PVC, APB, and APC [12]. A filter bank for the analysis was designed to enhance the QRS complex by separating the filtered ECG signal frequency ranges. The high and low frequencies were removed using a wavelet toolbox to process the ECG signal further and increase the S/N ratio [3]. The un-decimated wavelet transform (UWT) was used in 2014 to eliminate the noise in the ECG signals and obtain a clean electrical signal for diagnosis[13]. In 2015, another method was introduced to detect the QRS complex using a specific type of IIR filter, namely, the bi-reciprocal lattice wave filter [14].

The filter was designed based on a group of genetic algorithms and possessed some attractive characteristics. The first phase of design involved initiating the linear phase property to determine the best-fit reconstruction conditions. In the second phase, the filter was used to reduce the noise in the QRS complex. Finally, the realization of the designed filter was accomplished with only two multipliers, highlighting the reduced complexity of the method. The application of a neuro-based classifier on the output filter coefficients of the QRS-complex accompanied the whole procedure with excellent accuracy values[14]. Moreover, in 2015, many types of features were extracted from the amplitudes and intervals of different parts of the ECG signals [15]. Until 2016, a discrete wave transform (DWT) was implemented to detect the P wave and QRS complex [16]. The start logic machine and Pan-Tompkins algorithms to detect the R peak in the ECG signals were applied while comparing the difference between the R peak values from the two algorithms in each peak for the abnormalities and average signal[16].In 2016, the spatial-oriented method was used to complete the ECG analysis by reading only the essential features to assist physicians in diagnosis [17]. In 2017, twelve leads of ECG signals were provided to detect the QRS complex by applying Shannon's energy method. Shannon's energy was computed, and different thresholds were used to envelop Shannon's energy[18].The signal peak was then determined. Another method was also applied in 2017 for detecting and classifying the ECG abnormalities using the multi-model method [19]. The applied process was divided into three parts to detect the P wave, QRS complex, and S wave abnormalities. The first part was dedicated to data acquisition of the real-time ECG signal. Next, the data was processed while extracting the features of the ECG signal. The obtained features were used to classify the abnormality of ECG signals[19]. A comparison of FIR and IIR filters was applied in 2018 , as well as their performances from the ECG signal, is provided for better comprehension and display of the ECG data. For the execution operation, the ECG signals are loaded from the database into the MATLAB tool, and then these loaded signals are mixed with the simulated signal. The ECG signal and noise are then added. This additional signal is subjected to a time domain examination, and the appropriate design parameters for various digital filters are determined[20]. In 2021 The electrocardiogram systems were analyzed, designed, and implemented with optimal filters to suppress two types of unwanted noises from hardware, such as power delivery networks and miscellaneous peripherals. The reduction in sampling frequency could improve performance in ECG application areas, for example, by improving power and computation efficiency, leading to real-time ECG data processing.[21]

3. ECG SIGNAL CHARACTERISTICS ANDDATABASE

The Standard layout of the ECG signal [22] usually consists of the following waves (Fig. 1):

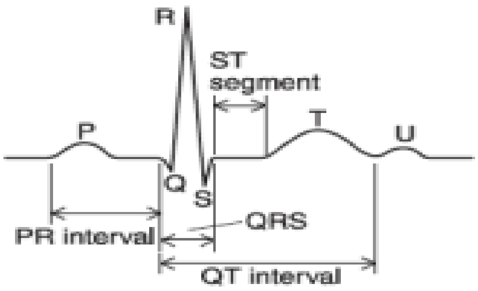


Fig. (1):- Standard ECG signal

3.1. P WAVE

At the beginning of each heart attack, the excitation begins to spread from the SA node located in the upper part of the right ventricle. The excitation occurs in the form of a wave in the atria. Depending on the voltage variances between the different spots on the skin, these differences can be recorded in high and low format with the electrical voltage generated by removing the polarization of the atria before shrinking[22].

3.2. PR STAGE

It represents the dividing line followed by a P wave and is located between the end of the P wave and the start of the QRS compound. Accordingly, the PR stage measures the time between the beginning of the atyine stimulation and the end of the ventricular stimulation[22].

3.3. COMPOUND QRS COMPLEX

It is a set of negative or positive deviations or waves associated with the loss of polarization in the ventricles and is measured from the start of the Q wave to the end of the S wave [20]. The discharge of the electrical charges from the ventricle, which is the start of heart muscle contraction, occurs quickly after the Q wave. The QRS compound is the transfer of excitation during the ventricles and the measurement of the physical effort produced by the demise of ventricular polarization before muscle contraction, i.e., when the wave of polarization disappears during the atria [22].

3.4. ST SEGMENT

The segment lies between the end of the S wavelet and the beginning of the P wave, which represents the time when the atypical contraction occurs[22].

3.5. T WAVE

This part represents the changes that occur before the ventricular prolapse[22].It is vitally important to mention that database collection is one of the essential parts of signal processing. The MIT-BIH Arrhythmia database directory of ECG signals from PhysioNet is selected [3].

4. THE CLASSIFICATION ACCORDING TO HEART DISEASE

The most common heart failures are as follows:

4.1. ATRIAL FIBERILLATION (AF): is the most commonly encountered clinical arrhythmia. It predominantly affects elderly patients [23].

4.2. CONGESTIVE HEART FAILURE (CHF): is a chronic, progressive disease in which fluid builds up around the heart, causing heart muscles to pump blood insufficiently. This serious health condition is marked by repeated hospitalizations and high annual mortality rates (25–40%) [24].

4.3. PULMONARY TB (PTB): is a heart disease caused by the Mycobacterium Tuberculosis bacteria. This type of bacteria can be easily transmitted from an infected person to a healthy one by various means. An individual may be infected with TB through the breathing, coughing, spitting, or sneezing of a TB patient. The bacteria attack the lungs, and the resulting lung infection is called Primary TB [25

4.4. LONG QT SYNDROME (LQTS): is a condition that affects the repolarization of the heart after the heartbeat. Repolarizing the heart can result in an increased risk of an irregular heartbeat, leading to palpitations, fainting downing, or sudden death [26].

5. FIR and IIR

Digital filters are a type of arithmetical technique that can be implemented in both hardware and software , Table 1. Show the difference between FIR and IIR Filter.[20]

Table (1):- The difference between FIR and IIR Filter

Characteristic	FIR	IIR
Phase	Linear	Non Linear
Stability	Stable	Oscillation
Precision Error	Very Small	Very High
Structure	No recursive	Recursive
Economy	Less	More
Storage Unit	No Feed Back	Feed Back
FFT	Can be Used	Can't be Used

5-Matched filter :

The correlation detector is also known as a matched filter. The fundamental premise of matched filtering is to design a correlation detector using prior knowledge about the intended signal .

The convolution y(n) of two discrete-time signals a(n) of length M samples and x(n) of length N samples can be defined as follows:

$$y(n) = a(n) * x(n)$$
$$= \sum_{k=-\infty}^{\infty} a(k)x(n-k) \quad \dots\dots\dots (1)$$

As we can see(from Eq.1) , convolution is commutative. Convolution is defined as "flipping" (reversing) one of the two signals in time, then sliding it over the other signal in time, multiplying the values of the two signals at eachtime sample, and summing the results.[27]

6- Artificial Neural Networks (ANN)

The essential basics will be covered surveying neural networks, to enable understanding of neural networks, to facilitate possible repetition of those neural networks introduced and successfully applied in medical imaging, and to inspire further development of neural networks.For medical imaging applications, there are various different neural network topologies available, but the Feed-forward network is one of the most frequent. They often include several levels, including one input layer, several hidden layers, and an output layer as shown in Fig (2) [28]

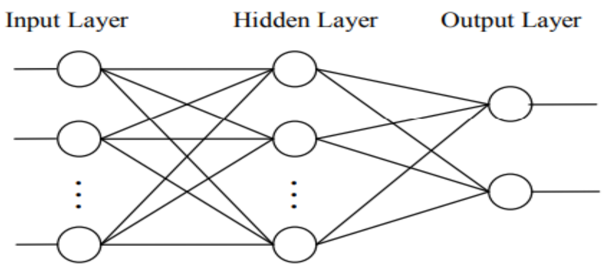


Fig. (2):- An example feed-forward network with a single hidden layer and two ou+tputs

7. Design Methodology

One significant problem of converting the analog ECG into the digital format is the noise interface caused by many factors such as the breathing muscle artifact and the 50Hz frequency power supply network. Due to the considerable influences of noise reduction on the efficiency of the ECG processing system, the analysis of the denoised ECG signal is usually accomplished by the initial process of filtering the 50Hz power line using the FIR filter[2] . It is important to remove (50Hz) from ECG signal before use it in the next stage which is (Artificial Neural Network) classification .The proposed digital filter consist of two parts , the first one is Discrete FIR Filter as shown in Fig.2 in this part the input signal (shown in figure 3) will be down sampling from (1280 sample) to (40 sample)

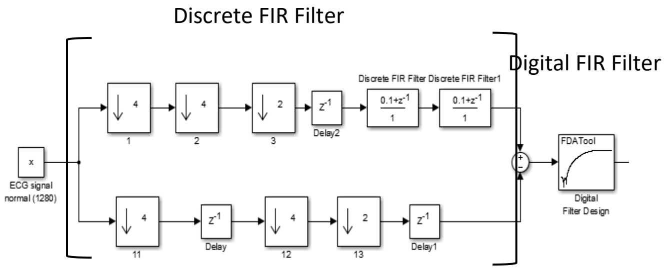


Fig. (2):- Matched Filter

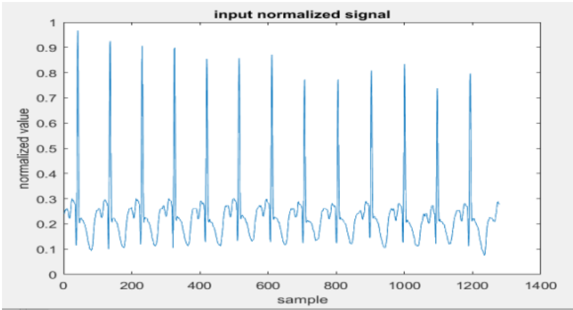


Fig. (3):- ECG input signal

In the second part of digital filter, a discretized version of the QRS complex of a standard ECG signal (Fig.4) is used to design a discrete-time response of a high pass FIR filter. The process of discretizing is achieved by equating the filter time-coefficients to the discretized version of the normal QRS. The FIR filter appears to take the following 39th order transfer function:

Fig. (4):- Using Normal ECG signal to simulate the FIR filter response

$H(z)$ =0.303589581 + $0.424670252z^{-1}$+$0.377651794z^{-2}$ +$0.35983433z^{-3}$ + $0.43765147z^{-4}$ + $0.305270033z^{-5}$ +$0.409837658z^{-6}$+ $0.42013987z^{-7}$+ $0.291954164z^{-8}$+ $0.539881937z^{-9}$ +$0.195446948\,z^{-10}$+ $0.451093283z^{-11}$+$0.481030149\,z^{-12}$+ $0.330591954z^{-13}$ + $0.039920619z^{-14}$+ $1z^{-15}$ +$0z^{-16}$ + $0.41730973\,z^{-17}$+$0.402018341z^{-18}$+ $0.420654441z^{-19}$+$0.322344428z^{-20}$+ $0.433853362z^{-21}$ + $0.339233505z^{-22}$ + $0.39220911\,z^{-23}$+ $0.433272221\,z^{-24}$+ $0.291932573z^{-25}$+$0.439169994z^{-26}$ + $0.376505704z^{-27}$ + $0.345642251\,z^{-28}$ + $0.438443117\,z^{-29}$

$+ 0.302197001\, z^{-30} + 0.517472918\, z^{-31} + 0.22386709 z^{-32} + 0.430965648\, z^{-33} + 0.455825175 z^{-34} + 0.290745102 z^{-35} + 0.426638575 z^{-36} + 0.370539562 z^{-37} + 0.358779999 z^{-38} + 0.44447763\, z^{-39}$ (2)

A matched filterwith filter order (12th order) is selected from the response of the overall FIR filter response given in Eq. (1). This equation represents the QRS complex as a high pass FIR response. It is implemented using Simulink in Matlab 2015A. The designed matched filter simulates the part of a QRS complex of a standard ECG signal is shown in Fig. 5. The filter has the following features :

1- Direct form of FIR structure
2- HPF Differentiator
3- FIR window method
4- $200Hz$ - $1200Hz$ Transition band
5- Sampling frequency of $2500Hz$.
6- Filter order 12

The resulting frequency response of the matched filter is shown in Fig. 5

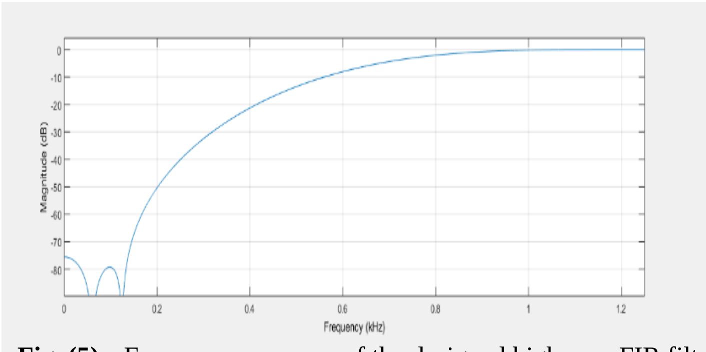


Fig. (5):- Frequency response of the designed high pass FIR filter

\

The ECG signals of the abovementioned heart diseases (AF, CHF, QT, and PTB) from the MIT-BIH Arrhythmia [29].After ECG input signal is down sampled in the Discrete FIR Filter it will be correlated with the transfer function (H(z) Eq. (2).) of Digital FIR Filter to measure the matching between twosignals (ECG input and H(z)).

The correlated output coefficients of the input ECG signals are measured. The filter output coefficients are applied to an artificial neural network (ANN) recognition system shown in Fig. 6 to verify and classify the input ECG signals .

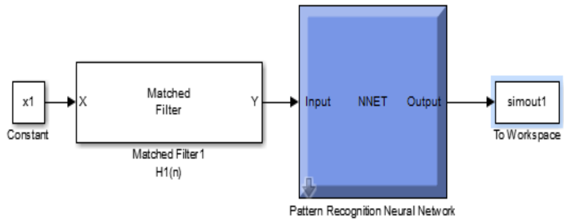
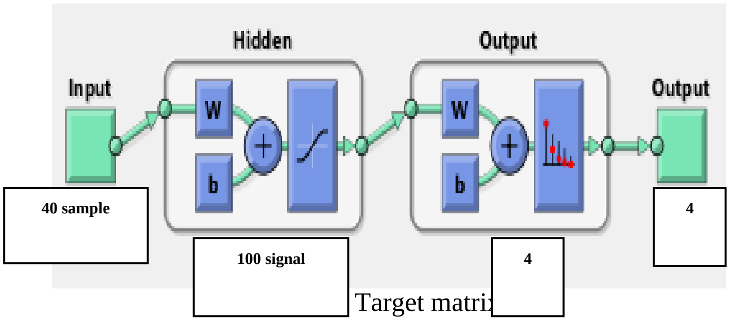


Fig. (6):- The overall designed classifier system

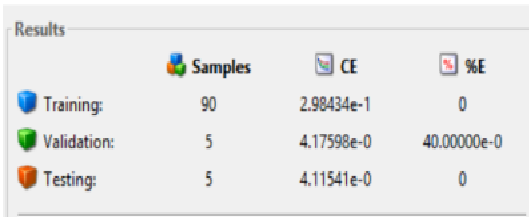
Fig.7 show the internal structure of artificial neural network in Matlab which is consist of four parts the first one is the input to (ANN) (40 sample) enter to the hidden part (second)designed to take (100 ECG signal) to classify it to (4) categories in output part (third) the input matrix is with (40, 100) while the output or target matrix is (4,4) as shown in Fig.8



1	0	0	0
0	**1**	**0**	**0**
0	**0**	**1**	**0**
0	**0**	**0**	**1**

Fig. (7):- the internal structure of ANN in Matlab

The input signals (100 Signal) is grouped to (90) as training , (5) validation and (5) testing as shown in Fig.9 for error calculation this classification gives minimum error of (40%)


Results

	Samples	CE	%E
Training:	90	2.98434e-1	0
Validation:	5	4.17598e-0	40.00000e-0
Testing:	5	4.11541e-0	0

Fig. (9):- Error calculation using ANN application in Matlab

7. RESULTS

The inputs and outputs of the neural network for the different tested disease signals are shown in Table.2, which indicates that the minimum amount of errors is found in the case of CHF disease while reaching the peak in QT disease.

Table (2): Inputs and outputs of neural network

	AF	CHF	PTB	QT	All
Input signal	25	25	25	25	%100
Output	20	21	17	10	%68
Error	5	4	8	15	%21

The results of the neural network training, validation, and testing are presented in Table. 3 From Artificial Neural Network Application in Matlab as shown in Fig (10, 11and 12) respectively ,the overall accuracy is up to 98%.

Table (3): The neural network results

	AF	CHF	PTB	QT	Acc
Training	100%	100%	100%	100%	100%
Validation	66%	66%	66%	66%	66%
Test	100%	100%	100%	100%	100%
All	100	92%	96%	100%	98%

Training Confusion Matrix

Output Classes

21 %23.3	0 %0.00	0 %0.00	0 %0.00	100 %0.00
0 %0.00	23 %25.6	0 %0.00	0 %0.00	100 %0.00
0 %0.00	0 %0.00	22 %24.4	0 %0.00	100 %0.00
0 %0.00	0 %0.00	0 %0.00	24 %26.7	100 %0.00
100 %0.00	100 %0.00	100 %0.00	100 %0.00	100 %0.00

Target Classes

Fig. (10):- The training confusion matrix

Validation Confusion Matrix

Output Classes

2 40%	0 %0.00	0 %0.00	0 %0.00	66 %33
0 %0.00	1 20%	0 %0.00	0 %0.00	50 %50
0 %0.00	0 %0.00	0 0.00%	0 %0.00	0 %0.00
0 %0.00	0 %0.00	0 %0.00	0 0.00%	0 %0.00
100 %0.00	100 %0.00	0 %0.00	0 %0.00	60 40%

Target Classes

Fig(.11):- The Validation confusion matrix

Test Confusion Matrix

Output Classes

2 40%	0 %0.00	0 %0.00	0 %0.00	100 %0.00
0 %0.00	1 20%	0 %0.00	0 %0.00	100 %0.00
0 %0.00	0 %0.00	1 20%	0 %0.00	100 %0.00
0 %0.00	0 %0.00	0 %0.00	1 20%	100 %0.00
100 %0.00	100 %0.00	100 %0.00	100 %0.00	100 40%

Target Classes

Fig.(12):-The Test confusion matrix

The comparison with the other recently-used methods for the ECG classification highlights the superiority of the proposed method in terms of accuracy is shown in Table4.

Table (4):- Comparison among different methods

Method	Accuracy
Ref. [6]	100%
Ref. [12]	97%-98%
Ref. [14]	95.9%
Ref. [16]	92.8% - 100%
Ref. [17]	87.196% - 95.424%
Ref. [19]	74%-100%
The proposed	98%

6. CONCLUDION

A matched filter is designed using a reduced version of the discrete-time response of a high pass FIR filter. In addition to its original extraction function, the designed high pass FIR filter can reduce the 50 Hz power supply interference. The best-fit correlated output feature coefficients have been obtained from different patients' ECG signals. An ANN-based recognition system is implemented to verify and classify the input ECG signals. In comparison with the other relevant methods, the designed filter reflects a high accuracy rate. The overall system can operate with 98% accuracy.

REFERENCES

W. V. Shi; T. N. Chang and M. C. Zhou.(2010) .Method to Detect Cardiac Abnormalities Based on Electrocardiography and Sinoatrial Pacemaker Model. International Conference on Mechatronics and Automation, August 4-7, , Xi'an, China.

S. Thulasi Prasad and S. Varadarajan .(2014) .Analysis of ECG Using Filter Bank Approach. Int. Journal of Engineering Research and Application, Vol. 4, Issue 1(Version 3), January, pp. 186-190.

J. C. Mannurmath and M. Raveendra . (2014) .MATLAB Based ECG Signal Classification . International Journal of Science Engineering Research and Technology Research, India, Vol. 3, Issue 7, pp 1946-1951.

G. A. Virgin and V. V. Baskar.(2018) .Conversion of ECG Graph into Digital Format . International Journal of Pure and Applied Mathematics, Sathyabama University, Chennai, Vol. 118, No. 17, pp. 469-484.

P. Sao, R. Hegadi and S. Karmakar. (2015).ECG Signal Analysis Using Artificial Neural Network. International Journal of Science and Research, National Conference on Knowledge, Innovation in technology and Engineering (NCKITE), Raipur, Chhattisgarh, India, 10-11 April , pp82-86.

S. Mukhopadhyay, S. Biswas, A. B. Roy, and N. Dey. (2012). Wavelet-Based QRS Complex Detection of ECG signal. International Journal of Engineering Research and Applications (IJERA), Vol.m2, Issue 3, May-Jan , pp. 2361-2365.

J. M. Abdul-Jabbar and A. M. Jasim. (2013).Design and Multiplierless Realization of ECG-Based Gaussian Wavelet Filter with Lattice Structures. Al-Rafidain Engineering College of Engineering, University of Mosul, Vol. 21, No. 2, April, pp 66-77.

M. K. Islam and A. N. M. M. Haque, G. Tangim, T. Ahammad, and M. R. H. Khondokar.(2012). Study and Analysis of ECG Signal Using MATLAB & LABVIEW as Effective Tools. International Journal of Computer and Electrical Engineering, Vol. 4, No. 3, pp 404-408.

O. C. Tellez and I. F. V. Lopez.(in press 2013). Towards a Formal Model for ECG Data Analysis and Decision Making. Universidad Autonoma de Sinaloa, Culiacan, Sinaloa, Mexico, Eureka-, Fourth International Workshop Proceeding.

J. M. Abdul-Jabbar and R. W. Hamad.(2014). Fuzzy Classification of ECG Signal Using a QRS-like FIR Filter Bank with lattice structure. Al-Rafidain Engineering College of Engineering, University of Mosul, Vol. 22, No.2, pp 1-11.

M. J. Vidya and D. Kavya.(2013). Analysis of ECG Signal Using MATLAB For The Detection of Ischemia. International Journal of Innovative Research and Development .Bangalore, India. Vol. 2, Issue 4, pp308-319.

D. Sambhu and A. C. Umesh .(2013). Automatic Classification of ECG Signals with Features Extracted Using Wavelet Transformation and Support Vector Machines. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, Vol. 2, Special Issue 1, pp 235-241.

B. S. Gayal and F. I. Shaikh. (2014) . Denoising of ECG Signal Un decimated Wavelet Transformer. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, Vol. 3, Issue 1, pp6896-6901.

J. M. Abdul-Jabbar and O. N. Saadi . (2015). Genetic-Based IIR Filter Design for Efficient QRS Complex Detection Using Neuro-Based Classifier. Al-Rafidain Engineering College of Engineering, University of Mosul, Vol. 23, No. 4, pp172-182.

S. Pokharkar and A. Kulkarni .(2015).ECG Real-Time Feature Extraction Using MATLAB. Journal of Technology and Science, Vol. 5, Issue 1, , pp. 1-4.

M. Pooyan and F. Akhoondi .(2016). Providing an Efficient Algorithm for Finding R Peaks in ECG Signals and Detecting Ventricular Abnormalities With Morphological Features. Journal of Medical Signal and Sensors, Vol. 6, No. 4, pp. 218–223.

P. J. M. Loresco and A. D. Africa.(2016). ECG Print-out Feature Extraction Using Spatial-Oriented Image Processing Techniques. Electronics & Electrical Engineering Department, Journal of Telecommunication, Electronics, and Computer Engineering, Vol. 10, No. 1-5,pp15-20.

H. Beyramienanlou and N. Lotfivand . (2017). Shannon's Energy Based Algorithm in ECG Signal Processing. Computational and Mathematical Methods in Medicine, Iran, Volume 2017, Article ID 8081361, 16 pages.

M. Ponnusamy and M.Sundararajan. (2017). Detection and Classifying ECG Abnormalities Using Multi-Model Method .Biomedical Research, India, Special Issue: Artificial Intelligent Techniques for Bio-Medical Signal Processing S81-S89.

Ms. Chhavi Saxena , Mr. Vivek Upadhyaya , Dr. Hemant Kumar Gupta , Dr. Avinash Sharma (2018) . Denoising of ECG Signals Using FIR& IIR Filter: A Performance Analysis. Proceedings on International Conference on Emerging Trends in Expert Applications & Security.

Ngoc-Thang Bui and Gyung-su Byun (2021). The Comparison Features of ECG Signal with Different Sampling Frequencies and Filter Methods for Real-Time Measurement. Institute of Engineering, Ho Chi Minh City University of Technology . https://doi.org/10.3390/ sym13081

John R. Hampton .(2013).The ECG made easy (8th ed.), Churchill Livingstone Elsevier, Emeritus Professor of Cardiology, University of Nottingham, UK.

Michael J. Quon MD and Louise Pilote MD MPH PhD .(2018). "Is Secondary Atrial Fibrillation Different? Or is Atrial Fibrilation Just Atrial Fibrillation? " ,Institute of the McGill University Health Centre, Montreal, Quebec, Canada.

William J Kostuk. (2001).Congestive heart failure: What can we offer our patients?. Canadian Medical Association Journal 165 (8) , page 1033

Jean-Luc Vachiéry, Ryan J. Tedford, Stephan Rosenkranz, Massimiliano Palazzini, Irene Lang, Marco Guazzi, Gerry Coghlan, Irina Chazova, and Teresa De Marco. (2018). Pulmonary hypertension due to left heart disease. The European Respiratory Society.

Ilan Goldenberg, MD, Arthur J. Moss, MD. (2008). Long QT Syndrome,. Journal of the American College of Cardiology Vol. 51.

Peter M. Narins and Grace A. Clark .(2016) Principles of Matched Filtering with Auditory Examples from Selected Vertebrates . University of California, Los Angeles .https://www.researchgate.net/publication/301266009

J. Jiang, P. Trundle and J. Ren .(2010) Medical Imaging Analysis with Artificial Neural Networks . Digital Media & Systems Research Institute, University of Bradford

The MIT-BIH Arrhythmia Database. On http://physionet.ph.biu.ac.il/physiobank/database/.