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ECG Signal Recognition Based on Lookup Table and Neural Networks

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ABSTRACT

Electrocardiograph (ECG) signals are very important part in diagnosis healthcare the heart diseases. The implemented ECG signals recognition system consists hardware devices, software algorithm and network connection. An ECG is a non-invasive way to help diagnose many common heart problems. A health-care provider can use an ECG to recognize irregular heartbeats, blocked or narrowed arteries in the heart, whether you have ever had a heart attack, and the quality of certain heart disease treatments. The main part of the software algorithm including the recognition of ECG signals parameters such as P-QRST. Since the voltages at which handheld ECG equipment operate are shrinking, signal processing has become an important challenge. The implemented ECG signal recognition approach based on both lookup table and neural networks techniques. In this approach, the extracted ECG features are compared with the stored features to recognize the heart diseases of the received ECG features. The introduction of neural network technology added new benefits to the system implementing the learning and training process.

Index Terms: Electrocardiograph signals, P-QRS, Healthcare, Heart diseases.

1. INTRODUCTION

Patients suffering from heart diseases need continuous healthcare especially for ECG monitoring and recognition to avoid dangerous of heart failure [1]. The reduction of heart attack depends on the fast identification of abnormal cardiac rhythms [2]. ECG is an effective diagnostic technique which is widely used by cardiologists [3]. ECG are electrical signals of the heart recorded by electrodes fixed on patient body [4]. ECG signals provide useful information about the rhythm and the operation of the heart. Heart beats extracted from ECG signals can be categorized into classes that are: Normal, atrial premature, and ventricular escape beats [5].

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Electrocardiographs are recorded by electrocardiograms that are very important for healthcare diseases [6]. These devices record electrical signal picked up by electrodes attached to certain parts of the patient body [7]. The signals recorded by the electrocardiograms at any moment are the sum of the all signals passing in cells throughout the heart [8]. Electrocardiogram consists of 12 leads which indicated 12 electrical views of the heart [9]. The first six leads represent the frontal plane leads; I, II, III, V_R, V_L and V_F. Leads I, II, and III are the standard leads and are find by [10]:

$$I = V_L - V_R \quad (1)$$

$$II = V_F - V_R \quad (2)$$

$$III = V_F - V_L \quad (3)$$

The other six leads are in the front of the heart; V_1, V_2, V_3, V_4, V_5, and V_6, these are recorded by the six electrodes placed on the chest of the patient [11].

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Electrocardiograms are concentrated on all issues associated with diseases of heart attack patients that used directly with clinical [12]. Recently, a reliable and automatic analysis and segmentation of ECG signals are required for health-care environments [13]. Computer based methods are suitable for processing and analyzing of ECG signals [14]. Artificial neural network techniques are used for analyzing different types of signals and tasks related to heart diseases [15]. Most of these tasks are associated to the detection of irregular heartbeats and irregular in recording process [16]. A back propagation neural network may apply in training stage to give a powerful pattern recognition algorithm [17].

Electrocardiograph (ECG) signals are very important part in diagnosis healthcare the heart diseases. The implemented ECG signals recognition system consists hardware devices, software algorithm and network connection. An ECG is a non-invasive way to help diagnose many common heart problems. A health-care provider can use an ECG to recognize irregular heartbeats, blocked or narrowed arteries in the heart, whether you have ever had a heart attack, and the quality of certain heart disease treatments. The main part of the software algorithm including the recognition of ECG signals parameters such as P-QRST. Since the voltages at which handheld ECG equipment operate are shrinking, signal processing has become an important challenge. The implemented ECG signal recognition approach based on both lookup table and neural networks techniques. In this approach, the extracted ECG features are compared with the stored features to recognize the heart diseases of the received ECG features.

2. ECG SIGNALS

Heart diseases are the well-known disease that affects humans worldwide [18]. Yearly millions of people die or suffered from heart attacks [19]. Early detection and treatment of heart diseases can prevent such events [20]. This would improve the quality of life and slow the events of heart failure [21]. The main benefit of the diagnosis is to record the ECG of the patient [22]. An ECG record is a non-invasive diagnostic tool used for the assessment of a patient heart condition [23]. The extraction of ECG features and combined that with the heart rate, these can lead to a fairly accurate and fast diagnosis [24].

Bioelectrical signals represent human different organs electrical activities and ECG signals are the important signals among bioelectrical signals that represent heart electrical activity [25]. Deviation or distortion in any part of ECG that is called arrhythmia can illustrate a specific heart disease [26]. The investigation of the ECG has been extensively used for diagnosing many cardiac diseases [27]. The ECG is a realistic record of the direction and magnitude of the electrical commotion that is generated by depolarization and repolarization of the atria and ventricles [28].

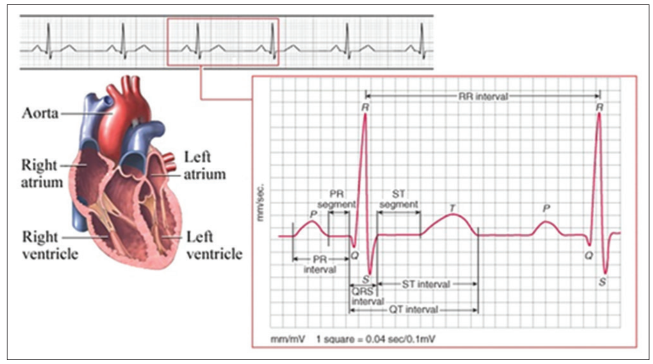

Fig. 1. Representation of electrocardiograph signals.

One cardiac cycle in an ECG signal consists of the P-QRS-T waves as shown in Fig. 1 [29,30]. The majority of the clinically useful information in the ECG is originated in the intervals and amplitudes defined by its features (characteristic wave peaks and time durations) [31,32]. ECG is essentially responsible for patient monitoring and diagnosis [33].

Normal rhythm produces four entities; P wave, QRS complex, T wave, and U wave in which each have a fairly unique pattern as shown in Fig. 1 [34,35]:

- P-Wave - Represents the movement of an electric wave from the sino atrial (SA) node and causes depolarization of the left and right atria.
- P-R segment - Represents the pause in electrical activity caused by a delay in conduction of electrical current in the atrioventricular (AV) node to allow blood to flow from the atria to the ventricles before ventricular contraction happen.
- QRS complex - Represents the electrical activity from the beginning of the Q wave to the end of the S wave and the complete depolarization of the ventricles, resulting to ventricular contraction and ejection of blood into the aorta and pulmonary arteries.
- S-T segment - Represents the pause in electrical activity after complete depolarization of the ventricles to allow blood to flow out of the ventricles before ventricular relaxation begins and the heart to fill the next contraction.
- Wave T - Represents the repolarization of the ventricles.

- Wave U - Represents the repolarization of the papillary muscle.

3. LITERATURE REVIEWS

Mohammed *et al.,* presented an ECG compression algorithm based on the optimal selection of wavelet filters and threshold levels in different sub bands that allow a maximum reduction of the volume of data guaranteeing the quality of the reconstruction. The proposed algorithm begins by segmenting the ECG signal into frames; where each image is decomposed into sub bands m by optimized wavelet filters. The resulting wavelet coefficients are limited and those having absolute values below the thresholds specified in all sub bands are eliminated and the remaining coefficients are properly encoded with a modified version of the run coding scheme [36].

Reza *et al.,* proposed compressed detection procedure and the collaboration detection matrix approach that used to provide a robust ultra-light energy focus for normal and abnormal ECG signals. The simulation results based on two proposed algorithms illustrate a 15% increase in signal to noise ratio and a good quality level for the degree of inconsistency between random and scatter matrices. The results of the simulation also confirmed that the Toeplitz binary matrix offered the best SNR performance and compression with the highest energy efficiency for the random array detection [37].

Ann and Andrés implemented an approach to classify multivariate ECG signals as a function of analyzing discriminant and wavelets. They used variants of multiscale wavelets and wave correlations to distinguish multivariate ECG signal models based on the variability of the individual components of each ECG signal and the relationships between each pair of these components. Using the results from other ECG classification studies in the literature as references that demonstrated this approach to 12-lead ECG signals from a particular database compares favorably [38].

Vafaie, *et al.,* presented a new classification method to classify ECG signals more precisely based on the dynamic model of the ECG signal. The proposed method is constructed a diffuse classifier and its simulation results indicate that this classifier can separate the ECG with an accuracy of 93.34%. To further improve the performance of this classifier, the genetic algorithm is applied when the accuracy of the prediction increases to 98.67%. This method increased the precision of the ECG classification for a more accurate detection of the arrhythmia [39].

Kamal and Nader, realized a practical means to synthesize and filter of ECG signal in the presence of four types of interference signals: first, from electrical networks with a fundamental frequency of 50 Hz, second, those resulting from breathing, with a frequency range 0.05–0.5 Hz, third musical signals with a frequency of 25 Hz and fourth white noise presented in the ECG signal band. This was accomplished by implementing a multiband digital filter (seven bands) of the finite impulse response multiband least square type using a programmable digital apparatus, which was placed on an education and development board [40].

Farideh *et al.,* explored combined discriminative ability of ECG/R signals in automatic staging. Basically, this approach classified that the wakefulness of slow wave sleep and REM sleep was classified using a vector support machine fed with a set of functions extracted from characteristics of 34 features and characteristics of 45 features. First part has produced a reasonable discriminatory capacity, while the second part has considerably improved the rating and the best results were obtained using third approach. We then improved the support vector machine classifier with the recursive feature elimination method. The results of the classification were improved with 35 of the 45 features [41].

Shirin and Behbood classified a patient's ECG cardiac beats into five types of cardiac beats as recommended by AAMI using an artificial neural network. This approach used block based on the neural network as a classifier. This approach created from a set of two dimensional blocks that are connected to each other. The internal structure of each block depends on the number of incoming and outgoing signals. The overall construction of the network was determined by the movement of signals through the network blocks. The network structure and weights are optimized using the particle swarm optimization approach [42].

Prakash and Shashwati, proposed an approach that attempts to reduce unwanted signals using a Minorization-Maximization method to optimize total signal variation. The unsuccessful signal is then segmented using the bottom-up approach. The obtained results show a significant improvement in the signal-to-noise ratio and the successful segmentation of the ECG signal sections. The extension of the heel depends on the smoothing parameter of Lamda. As this approach was implemented for complete signal, then only 18 dB of signal to noise ratio was achieved [43].

Aleksandar and Marjan, focused on a new algorithm for the digital filtering of an electrocardiogram signal received by stationary and non-stationary sensors. The basic idea of digital processing of the electrocardiogram signal is to extract the heartbeat frequencies that are normal in the range between 50 and 200 beats/min. The frequency of the extracted heart rate is irregular if the rate increases or decreases and serves as evidence for the diagnosis of a complex physiological state. The environment can generate a lot of noise, including the supply of electrical energy, breathing, physical movements, and muscles [44].

Kumar *et al.,* proposed an automated diagnosis of coronary artery disease using electrocardiogram signals. Flexible Analytical Wavelet Transform technology is used to break down electrocardiogram effects. The Cross Information Potential parameter is calculated from the actual values of the Flexible Analytical Wavelet Transform decomposition detail coefficients. For diagnosis of coronary artery disease subjects, the mean value of the Cross Information Potential parameter is higher in the comparison toner subjects. The statistical test is applied to check the discrimination capacity of the extracted functionalities. In addition, the functionality is fed to the least squares support vector machine for sorting. The classification accuracy is calculated at each decomposition level from the first decomposition level [45].

Al-Ani, explained that ECG waveform is an important process for determining the function of the heart, so it is useful to know the types of heart disease. The ECG chart gives a lot of information that is converted into an electrical signal containing the basic values in terms of amplitude and duration. The main problem that arises in this measurement is the confusion between normal and abnormal layout, in addition to certain cases where the P-QRS-T waveform overlaps. The purpose of this research is to provide an effective approach to measure all parts of the P-QRS-T waveform to give the right decision for heart function. The proposed approach depends on the classifier operation that based mainly on the features extracted from electrocardiograph waveform that achieved from exact baseline detection [46].

Nallikuzhy and Dandapat, explored an efficient technique to improve a low resolution ECG by merging fragmented coding and the learning model of the common dictionary. An enhance model is applied on low resolution ECG using previously learned model in order to obtain a high resolution full estimate of 12-lead ECG. This approach was applied based on the dictionary in which the common dictionary contains high and low resolution dictionaries regarding to the high and low resolution ECG and is learned simultaneously. Similar fragmented representation for high and low resolution ECGs was generated using Joint dictionary learning. Mapping between the scattered coefficients of the high and low resolution ECGs was also learned [47].

Han and Shi presented an efficient method of detection and localization of myocardial infarction that combines a multi-lead residual neural network structure (ML-ResNet) with three residual blocks and a function fused by 12-lead ECG recordings. A single network of characteristic branches was formed to automatically learn representative characteristics of different levels between different layers, which exploit the local characteristics of the ECG to characterize the representation of spatial information. Then, all the main features are merged as global features. To evaluate the generalization of the proposed method and clinical utility, two schemes are used that include the intra-patient scheme and the inter-patient scheme. The obtained results indicated a high performance of accuracy and sensitivity [48].

Abdulla and Al-Ani, implemented a review study classification for ECG Signal. This work aimed to investigate and review the use of classification methods that have been used recently, such as the artificial neural network, the convolutional neural network, discrete wavelets transform, support vector machine and K-Nearest Neighbor. Effective comparisons are presented in the result in terms of classification methods, feature extraction technique, data set, contribution, and some other aspects. The result also shows that convolutional neural network has been used more widely for ECG classification as it can achieve higher accuracy compared to other approaches [49].

Abdulla and Al-Ani, explained an automatic ECG classification system which is difficult to detect, especially in manual analysis. An accurate classification and monitoring ECG system was proposed using the implementation of convolutional neural networks and long-short term memory. Learned features are captured from the CNN model and passed to the LSTM model. The output of the CNN-LSTM model demonstrated superior performance compared to several of the more advanced ones cited in the results section. The proposed models are evaluated on the MIT-BIH arrhythmia and PTB diagnostics datasets. A high accuracy rate of 98.66% in the classification of myocardial infarction was obtained [50].

4. METHODOLOGY

The methodology of this approach is divided into three parts: ECG signals recognition approach, ECG feature extraction

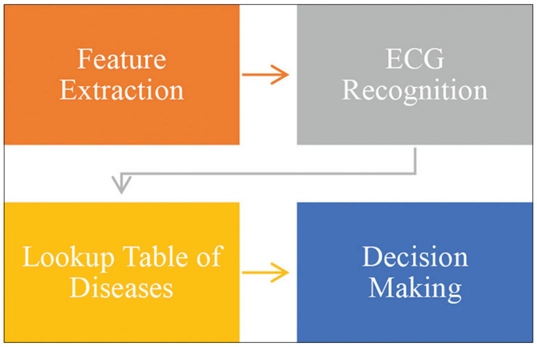

Fig. 2. Electrocardiograph recognition approach.

and neural network architecture. In addition, the used data are images selected with different heart diseases.

The main objective of introducing forward propagation neural networks in this work is to determine the main component values of the ECG signal, which are seven values (QRS complex, QT interval, QTCB wave, PR interval, P wave, RR interval and PP interval) and to compare that with the table that carries the standard values. Depend on this comparison, it is possible to make an accurate decision about whether the ECG signal is normal or abnormal.

4.1. ECG Signals Recognition Approach

The ECG signals recognition approach is implemented through the following stages (Fig. 2):

- Feature extraction stage in which ECG signals parameters (amplitude and time interval) will be extracted from the electrodes.
- ECG recognition stage in which the extracted parameters of ECG are applied through neural network that specified the diseases associated with these parameters.
- Lookup table stage in which the constructed lookup table is associated with the list of specified heart diseases.
- Decision making stage in which take the decision of which type of heart diseases are related.

4.2. ECG Feature Extraction

Tracing of ECG signal on the special recognition is very important to extract the values of the direct parameters. The main advantage of ECG feature extraction operation is to generate a small set of features that achieve the ECG signal. ECG feature extraction operation is implemented through many steps as shown in Fig. 3. The first step is preprocessing in which ECG graph will be cleaned and resized. The second step focusing on thinning filter in which the ECG signal will be better quality, in addition this step will eliminate the scattering pixels around the original signal. The third step

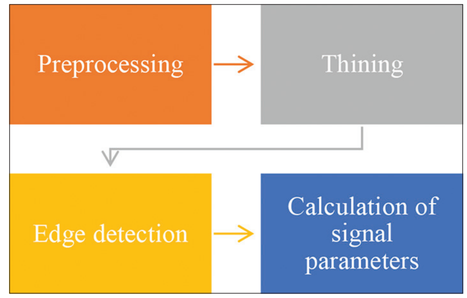

Fig. 3. Electrocardiograph feature extraction.

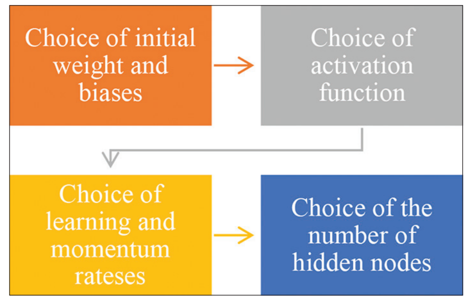

Fig. 4. Design of neural network architecture.

concentrates on edge detection that detects the original ECG signal. In addition, this indicates the duration and amplitude of each ECG signal part. Fourth step is to calculate the required parameters of ECG signal that related on duration and amplitude of each part of ECG signal.

4.3. Neural Network Architecture

Proper neural network architecture is used to be efficient and work in a wide range of conditions. It is necessary to choose network parameters such that the obtained ECG system is acceptable for theoretical and practical settings. Furthermore, this neural network is an application-oriented system and the design is done with the selection of the network architecture. In this case, many parameters are selected as below (Fig. 4):

- Choice of initial weight and biases: The choice of initial weight will influence how quickly the system coverage? The values of the initial weights must not be too large or too small to avoid out of region condition. The weights and biases of ECG network in learning phase are initialized randomly between -0.5 and 0.5.
- Choice of activation function: The ECG used neural network of sigmoid function which has simple derivative and nonlinear property. The sigmoid range of output lies between zero and one.
- Choice of learning and momentum rate: For low learning rate, the neural network will adjust their weights gradually, but the convergence may be slow, while for high learning

rate the neural network has big changes that are not desirable in a trained network. The network consists of 5 nodes in input layer, 80 nodes in hidden layer, and 4 nodes in output layer.

- Choice of the number of hidden nodes: The number of hidden nodes in the hidden layers is varied from 5 nodes to 125 nodes, while keeping the learning rate and momentum rate constant at nominal values (learning rate = 0.7 and momentum rate = 0.9). Backpropagation neural network algorithm is used for ECG system to achieve a balance between correct response to the trained patterns and good responses to new input patterns.

The forward propagation algorithm starts with the presentation of input pattern to the input layer of the network and continues as activation level calculations propagate forward through the hidden layers. Every processing unit (in each successive layer) sums its inputs and applies the sigmoid function to compute its output. Then the output layer of the units produces the output of the network.

Suppose the total input S_j to unit $_j$ is a linear function of the states of units a_i which is equal to the activation levels of the neurons in the previous layer that is connected to unit $_j$ through the weights W_{ji} and the threshold, θ_j of unit $_j$ where:

$$S_j = \sum_i a_i W_{ji} + \theta_j \tag{4}$$

The state of (y) of a unit is a sigmoid function of its total input S.

$$y_i = f\left(S_j\right) = \frac{1}{1 + e^{-s}} \tag{5}$$

The resulting value becomes the activation level of neuron $_j$. once the set of the outputs for a layer is found, it serves as an input to the next layer. This process is repeated layer by layer until the final set of network output is produced.

The backward propagation algorithm indicated by error values and these are calculated for all processing units and the weight changes are calculated for all interconnections. The calculations begin at the output layer and progress backward through the network to the input layer.

The error value is simple to be computed for the output layer and somewhat more complicated for the hidden layers. If unit $_j$ represents the output layer, then its error value is given by:

$$\delta_j = \left(t_j - a_j\right) F'\left(S_j\right) \tag{6}$$

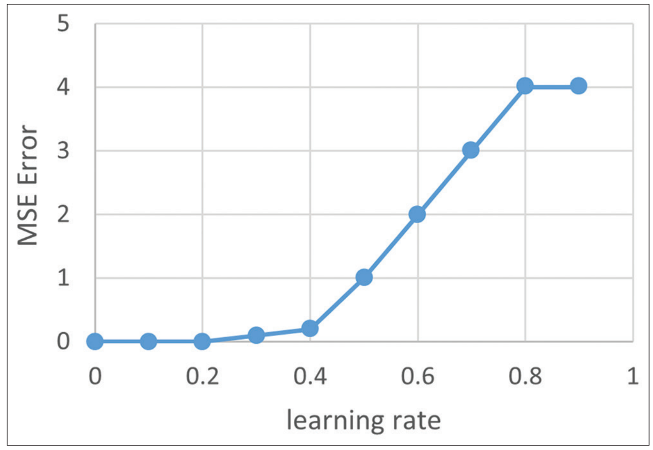

Fig. 5. The relation between learning rate and mean square error.

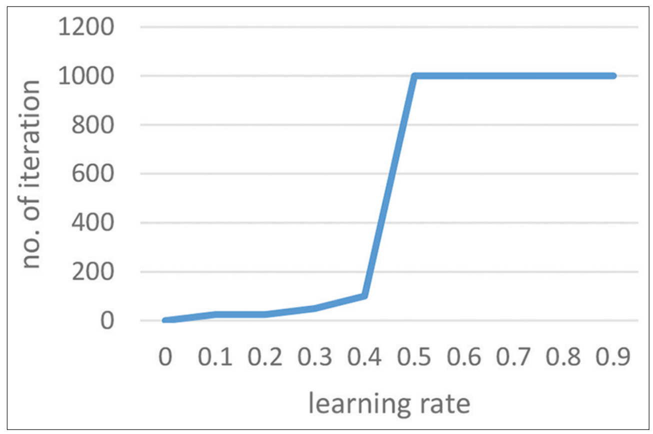

Fig. 6. The relation between learning rate and number of iteration.

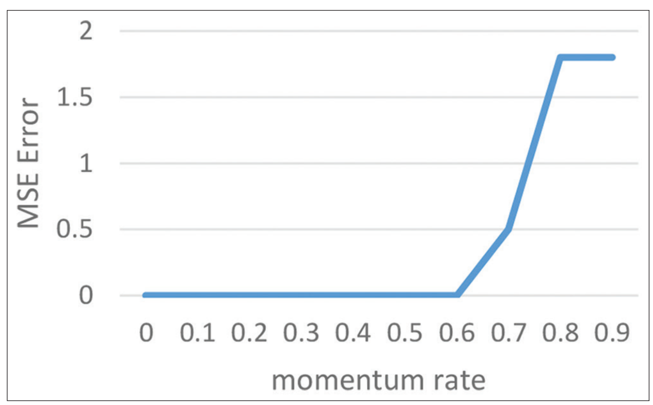

Fig. 7. The relation between momentum and mean square error.

Where:

- t_j is the target value for unit $_j$.
- F' (S_j) is the derivative of the sigmoid function F.
- a_j is the output value for unit j.
- S_j is the weighted sum of inputs to j.

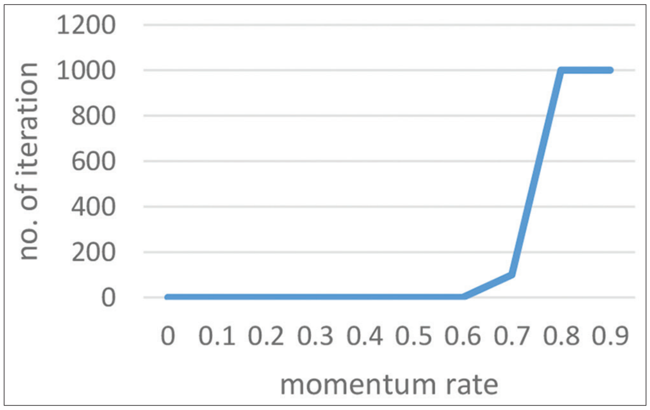

Fig. 8. The relation between momentum and number of iteration.

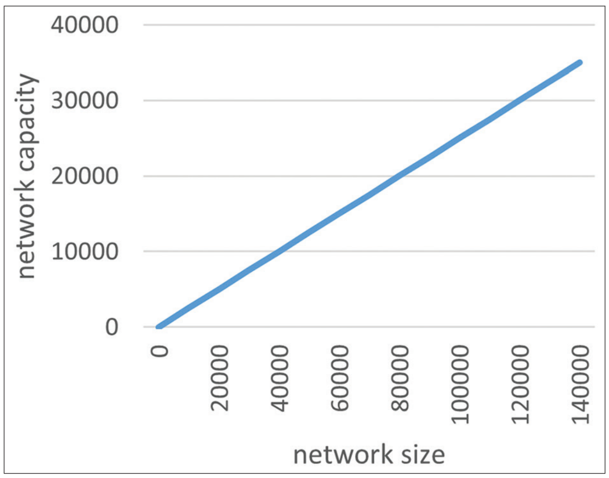

Fig. 9. The relation between network size and network capacity.

5. RESULTS AND DISCUSSION

Fig. 5 gives the relation between learning rate and mean square error (MSE). The learning rate value is laying between zero and one and the commonly used range is in between 0.25 and 0.75. At this active rang of learning rate, the calculated MSE is so small and laying in the range 0.1 and 3.5. Fig. 6 shows the relation between learning rate and the number of iteration. At this figure it is clear that when the learning rate is equal to 0.5, then the number of iteration is 1000 and still saturated at this number of iteration as learning rate increases.

Fig. 7 shows the relation between momentum rate and MSE. The momentum rate value is laying between zero and one and the commonly used range is around 0.9. At this figure MSE still zero up to the momentum rate value is equal to 0.8 at which MSE is about 1.8 and then saturated at this value. Fig. 8 shows the relation between momentum rate and number of iteration. At the momentum rate value of 0.8 the number of iteration is reached to 1000 and still saturated at this value.

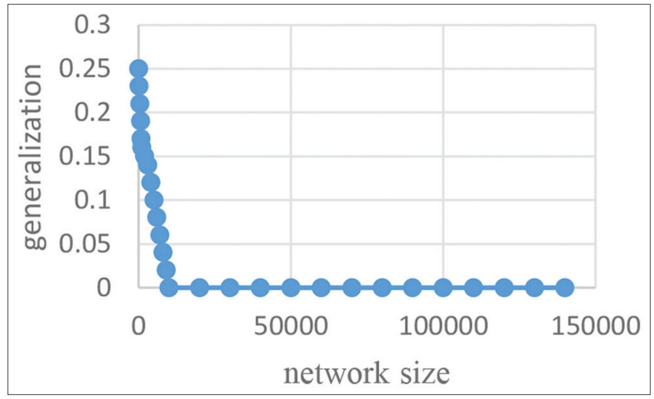

Fig. 10. The relation between network size and generalization.

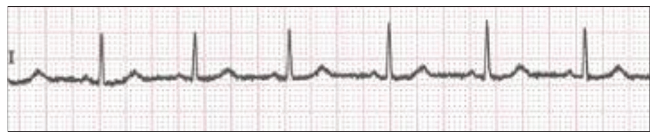

Fig. 11. Normal electrocardiograph signal.

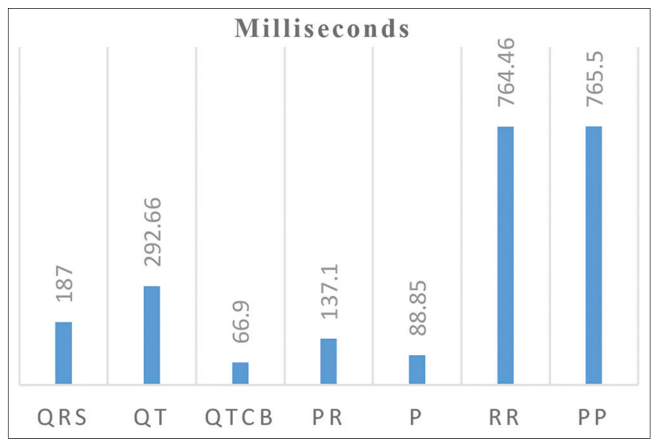

Fig. 12. Final diagnosis of electrocardiograph signals (normal case).

Fig. 13. Sinus tachycardia electrocardiograph signal.

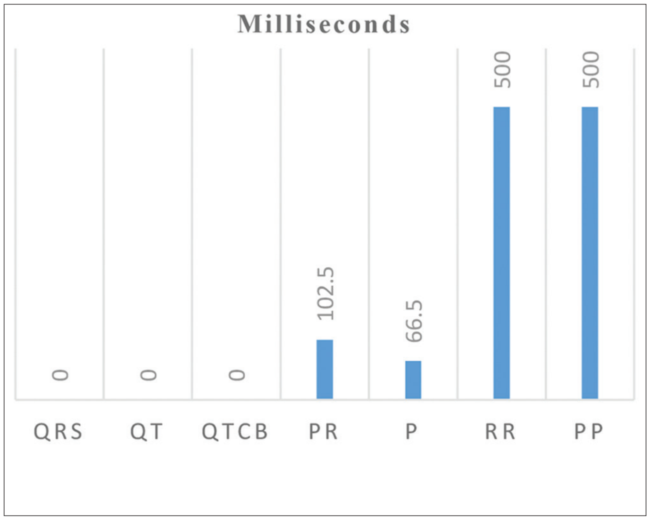

Fig. 14. Final diagnosis of electrocardiograph signals (sinus tachycardia case).

Fig. 9 demonstrates the relation between network size and network capacity. At this figure it is clear that there is a linear relation between network size and network capacity. As the network size increases up to 140,000 it is clear that the network capacity increases up to 35000. Fig. 10 shows the relation between network size and generalization. At this figure it is clear that the maximum generalization is obtained at starting point of the network size. Then the generalization decreases when the network size increases. On the other hand, the zero generalization is obtained at the network size equal to 1000.

Fig. 11 presents the normal case of ECG signal. Fig. 12 shows a normal patient having sinus normal rhythm in which the measurement ECG parameters are: QRS: 189.00 ms, QT: 292.66 ms, QTcB: 66.90 ms, PR: 137.10 ms, P: 88.85 ms, RR: 764.46 ms, and PP: 775.50 ms, this case indicated that the patient diagnosis is normal.

Fig. 13 deals with the sinus tachycardia case of ECG signal. Fig. 14 shows another patient having sinus tachycardia rhythm in which the measurement ECG parameters are: QRS: 0.0 ms, QT: 0.0 ms, QTcB: 0.0 ms, PR: 102.5 ms, P: 66.5 ms, RR: 500 ms, and PP: 500 ms, this case indicated that the patient diagnosis is sinus tachycardia.

6. CONCLUSIONS

The diagnosis of heart diseases depends largely on ECG, in addition to other devices that give special properties and parameters that leading to great importance in the field of healthcare. Measurements of ECG signals lead to the identification of problems experienced by people with heart disease. Real-time ECG diagnosis has several advantages as it is important in sharing private information in healthcare systems especially for heart diseases. The implemented approach accompanies the properties of features extracted from the lookup table and properties of neural networks. The feature extraction step verifies the features from the received ECG and neural networks give good responses to the new input patterns. The applied approach gives accurate detection of ECG signals as well as good quality of recognized ECG signals.

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