LEARNING NEURAL NETWORKS FOR DETECTION AND CLASSIFCATION OF BIOMEDICAL SIGNAL SECTION (ECG)

Assit. Prof. Dr. Hanan A. R. Akkar Ms.c. Hussain Karrem Khleaf
Department of Electrical and Electronic Engineering
University of Technology
Baghdad / Iraq
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ABSTRACT

In this paper back-propagation neural network is presented for pattern recognition of ECG wave analysis and diagnosis, where training is applied for some common heart disease. Linear Predictive Coding (LPC) is used as a proposed method to compress the data, which were extracted from electrocardiogram, ECG paper. LPC method is tested before using it in this work, where it has succeeded in verifying coding operation to the signals. This method is efficient to reduce the ANN size used in this work. Data used are obtained from all currently available ECG databases, which were previously collected from different fields, such as Internet sites, different hospitals and some publications related with this field. The ECG samples were processed and normalized to produce a set of data that was applied to LPC and then to Artificial Neural Network (ANN). The results obtained are compared with the classifications made by a Doctor, where these results proved an efficient diagnosis with good performance and accuracy. Simulation results are obtained using technical (MATLAB) package implemented on IBM PC.

كشف و تصنيف الإشارات الطبية (ECG) باستخدام الشبكات العصبية

ا.م.د.حنان عبد الرضا عكار المدرس المساعد حسين كريم خليف
الجامعة التكنولوجية /قسم الهندسة الكهربائية والالكترونية
بغداد/ العراق

الملخص:- تم في هذا البحث استخدام أسلوب المعالجة المسبقة للمعلومات المستخرجة من إشارة تخطيط القلب (ECG) قبل اعتمادها كعناصر دخل إلى الشبكات العصبية. حيث تم استخدام طريقة تشفير التوقع الخطية (Linear Predicative Coding (LPC)) كدالة لضغط البيانات المستخرجة مسبقا. لقد تم اختبار هذه الطريقة قبل أن تعتمد في هذا العمل, حيث أثبتت نجاحها في عملية التشفير للإشارات. مما عكست فائدة كبيرة في تقليص حجم الشبكة العصبية المستخدمة . وقد استخدمت طريقة الانتشار العكسي (Back-propagation neural network) كونها أحد الطرق الكفوءة في عملية تمييز الأشكال (pattern recognition) ضمن التدريب بوجود مشرف (supervised training). تم تدريب هذه الشبكة على عدد من الأمراض الشائعة للقلب. حيث تم جمع عدد من هذه المعلومات من خلال المواقع المختصة في الانترنيت وكذلك من خلال المسح الميدانيّ لعدد من المستشفيات وكذلك من خلال بعض المنشورات في هذا الحقل. حيث تم اختيار البيانات الجيدة منها بالاستعانة ببعض الأطباء والمختصون في هذا المجال. تمت مقارنة نتائج تشخيص الشبكة مع نتائج التشخيص من قبل الطبيب المختص وكانت نتائج التشخيص عالية جداً, من حيث أداء البرنامج في ترجمة الإشارة الكهربائية وتشخيص الحالة المرضية للقلب. حيث تم استخدام المختبر الرياضيMATLAB والتقنيات المتوفرة فيها لتنفيذ هذا العمل كأحد لغات البرمجة المستخدمة في تطبيقات ا لبحوث العلمية.

1- INTRODUCTION

The ECG diagnosis can be a difficult problem and misdiagnosis does occur some time. The use of the computer-based methods is, therefore, valuable in order to analyze and interpret the ECGs. Artificial Neural Networks (ANN) is one of the computer-based methods for early diagnosis of heart attack, and it can be regarded as one of the good techniques in this field and has primarily been considered for classification of ECGs into different diagnostic groups. It has been shown that Ann's for specific issues can perform better than both experienced cardiologists and ruled criteria [1]. The advantage of using 12-lead ECG is the immediate availability and the possibility of an automated interpretation using computer software bundled with the ECG recorder. An additional advantage will certainly be obtained if the ECG interpretation method can explain the behind its finding, thereby, increasing the support for the physician diagnosing the patient [2].

Several research groups are involved in carrying out different types of work in computer aided interpretation of biomedical signals (ECG), and some of the research under taken in the last decade include:

In 1991, Sulaiman [3], made a general comparison of the noise sensitivity of nine QRS from ECG signal detection algorithms. In 1994, Jager F., Moody G. B., Divjak S., and Mark R.G. [4], developed algorithms for detecting transient ischemic ST segment changes. In 1996, Ziad. S. A. [5], used a proposed neural networks for ECG processing, the research shows a new approach to process the cardiac electric signals (ECG), by using neural networks. In 1997, Rosaria S. and Carlo M ,[6] .used ANN structures combined with different pre- and post-processing techniques that are designed and evaluated for arrhythmia classification ,ischemia detection, re-cognition of chronic myocardial diseases. In 1997, M. Ohlsson, H. Holst and L. Edenbrandt [7], showed a new approach, which depends on the comparison between the current ECG and a previous one of the same patient, as an aid in the decision making.

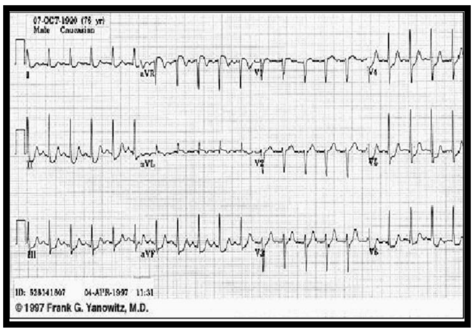
In 1999, Szu H. [8], developed wavelet application and neural network to design a diagnostic system for ECG signals. In 2000, Steven E and Harold H. [9], used independent component analysis (ICA) to ECG signals for improved detection of abnormal conditions in the heart. In 2001, Syed Khursheed H. [10], developed system was part of the Computerized Patient Monitoring System. In 2001, Henrik H., Lars E .and Mattias O. [2], they used ANN to detect signs of acute myocardial infarction in ECGs. In 2001, Itay L .and Yossi H. [11] ,classification of ECG signals by unsupervised learning algorithms. And in 2002, Ann F. S[1] used ANN as diagnosing system of ECG signals, and used FFT together with cross correlation to perform all component analyses of the ECG signal.

In this paper, we will study trainable layered neural networks employing the input data. In the case of layered network training, the error can be propagated into hidden layers so that the output error information passes back ward. This mechanism of back ward error transmission is used to modify the synaptic weights of internal and input layers. The back propagation algorithm is used throughout this paper for supervised training of multilayer **FFNN** [12-14].

Laboratory data converted from analog to digital form are useful to use in microcomputer. And the pre-processing enhances the ability of biomedical physics to subject these data to complex analysis, which would not be possible otherwise. The following sections illustrate the pre-processing steps and how the ANN designed and used, in more detail. The data used for ECG diagnoses in this work are collected from different locations, such as Hospitals and Internet (MIT-BIH Arrhythmia database), then selecting the suitable data sets, to design the required ANN system. This problem represents the main problem in the work.

2.Primarily Data Sets

The optical scanning technology is used to find the data sets in this work. This technology resolves images to an optical resolution of (72) pixel (dots) per inch (dpi)[4].The ECG signal paper is converted into image stored in many types of format files such as (bmp, jpg, and gif). The first step in this work is receiving this image and converting it into a series of numbers (or special matrix) and these values in this matrix are proportional to the brightness (or gray level) of the image. After completing the first step of the ECG signal shows on the monitor. And by using mouse, select the lead that you want to test, this selected lead is achieved by using left mouse button (drag and drop) as shown in figure (1). Then inter the number of lead as shown below) :I=1, II=2, III=3, VR=4 , VL=5, VF=6, V1=7, V2=8, V3=9, V4=10, V5=11, V6=12 .Using these numbers is useful to give good optimization of the Ann's.



(a)

(b)

Figure (1) a) Image of the ECG signal paper. b) Image of the lead II segment selects.

3. Steps of the Pre-Processing

For each lead segment selected from ECG signal papers many pre- processing steps have been carried out in order to extract the final diagnosing data. These steps are as follows:

1. Conversion and normalization of the desired signal from gray values into binary values.
2. Separation of the desired signal from its background.
3. Some types of filters must be applied for these images.
4. The signal line must be of finite thickness.
5. Signal period identification.
6. Computing the LPC coefficients of the lead signal.

3.1 Conversion and Normalization of ECG Lead Signal

After receiving the ECG signal image from scanning devise and storing this image in file format such as bmp format in the memory of computer. The first step in the program is conversion of the image into data vector stored in spatial matrix, the values in this matrix are converted from gray values into vector values that are used as numbers in the program. The values in this matrix vector (row and column) are representation for intensity of light as amplitude of the ECG signal image. The range of these values is between 0 and 255, where 0 values is representation of black color and the 255 is a representation of white color, and all other values between them are representation of varying gray color. Now, the normalization of these values (image matrix) is a second step. This is achieved by dividing all the values in the image matrix by the maximum value in the same matrix. Now, all the values in the image matrix are between 0 and 1, and it is easy to deal with them in next step.

3.2 Lead Signal Extraction

To extract any lead signal from its background grid line of the paper must use a spatial process, this process is called threshold filtering, and it operates on canceling the light colored points. The image in the first step is converted to gray level values depending on the intensity of the light. Normally, the lead signal points are dark (or heavy dark) corresponding to the background grid lines. In this filter, a threshold level between (0.2 and 0.5) is chosen. Any value that is chosen between these two values is corrected to cancel the undesired signal from the image, depending on the type of scanning image. If the image is scanned with high intensity of light or low brightness (or gray levels near black color), sometime some regions consist same value or near that represented original signal. In this case the value most be selected 0.2 (or near). The values in the image matrix are between 0 and 1,with respect to gradual black and white colors. After completing the process, the matrix values are in binary form (only consist of zeros and ones).

3.3 Noise Removal

After the desired signal is extracted in the pervious step, normally the noise may be presented with this image. There are several sources for this noise, which can be introduced into an image, depending on how the image is created. If the ECG signal paper is scanned by the scanner device at very high resolution, the colors in this image become near to the black color (high intensity in light), that represents the desired signal in the image. The scanner itself can also introduce noise. Such as dotes or grain with the desired signal image.

3.4 Slandering the Signal Line

In any image scanning, the signal lines are several pixels wide, and these pixels cause many values in the amplitude and time that can be read. In this step the method that can be used to achieve the slandering signal line is time slice. The time slice is a vector of pixel positions containing values transmitted by the scanner as it scans the signal line. The time lit pixel refers to a pixel whose value is the signal line.

3.5 Signal Period Identification

After completing the desired signal in a matrix of data, the next step in this work is to find the two distinct, which represent the highest adjacent protrusion in the specific lead signal.

This step involves finding the first point which presents the maximum or minimum amplitude lead signal, and records its value and location. After detecting the location of the first peak or bottom points, the program starts searching for the next peak or bottom points, which has a threshold level. This threshold level equals 90% of the amplitude of the first detected point. The use of such threshold level is to record ECG signal peak point, which is generally not repeatable in their amplitudes.

4. Computing the LPC of the Lead Signal

The technique used in this paper presents a method to compress signal data, which are used in the next stage as input to the neural network. The LPC is one of the most useful methods for encoding good quality signal at a low bit rate. In this step, the software will receive data of the lead signal as a signal vector for one period, and by using LPC will compress this data and convert them to a new form consisting of ten numbers only, because these received data are representation of discrete time signal (vector signal). If these sampling signals are used directly without any process as the input to the ANN, this will be required to use large number of neurons in the input layer. By using LPC technique. The user will reduce these data numbers to any small numbers that can be limiting. These data are as complex numbers having same characteristics of the original signal. For these complex numbers will be given the magnitude values. Now the program will be add to these magnitude values the type of the lead signal.

Finally an example of the training data set for one normal cases are illustrated in table(1) and table(2). Before and after using training as input to the ANN, and in order to get good performance for the ANN 57 training data sets are used for five-disease state (15 normal cases. 17 MI cases, 14 Angina cases, 5 RBBB cases and 6 LBBB cases). These 57 cases are difficult to collect and carefully selected.

Table (1) One of the training data sets (normal case) before add the lead type.

leads	Training Data Sets for One of the Normal Cases.									
I	0.7378	0.0648	0.0768	0.0216	0.0495	0.0265	0.0262	0.0165	0.382	0.0506
II	0.4685	0.0812	0.0069	0.0638	0.0504	0.0455	0.0507	0.0423	0.0534	0.0777
III	0.7429	0.0561	0.0422	0.1700	0.1412	0.0802	0.0080	0.0267	0.0502	0.0549
VR	0.9106	0.0302	0.0322	0.0366	0.0129	0.0257	0.0128	0.0008	0.0061	0.0017
VL	0.4815	0.2180	0.2495	0.1503	0.2136	0.1474	0.0025	0.2211	0.0146	0.1124
VF	0.8035	0.2711	0.1783	0.0177	0.0181	0.0270	0.0695	0.0184	0.0386	0.0618
V1	0.8883	0.7827	0.6826	0.5872	0.4960	0.4081	0.3232	0.2404	0.1594	0.0794
V2	0.9023	0.8066	0.7127	0.6202	0.5292	0.4392	0.3503	0.2620	0.1744	0.0871
V3	0.3509	0.1749	0.1365	0.0880	0.0624	0.0432	0.0298	0.0202	0.0130	0.0035
V4	0.4900	0.0395	0.1225	0.0680	0.0590	0.0435	0.0313	0.0263	0.0190	0.0198
V5	0.7967	0.6331	0.5013	0.3945	0.3074	0.2357	0.1758	0.1247	0.0798	0.0389
V6	0.8515	0.7212	0.6066	0.5049	0.4142	0.3324	0.2577	0.1886	0.1235	0.0611

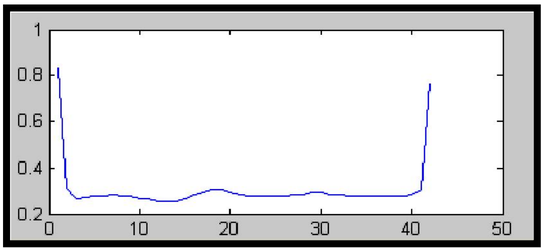
Table (2) Final form of the training data sets (normal case).

leads	Training Data Sets for One of the Normal Cases.									
I	1.7378	1.0648	1.0768	1.0216	1.0495	1.0265	1.0262	1.0165	1.382	1.0506
II	2.4685	2.0812	2.0069	2.0638	2.0504	2.0455	2.0507	2.0423	2.0534	2.0777
III	3.7429	3.0561	3.0422	3.1700	3.1412	3.0802	3.0080	3.0267	3.0502	3.0549
VR	4.9106	4.0302	4.0322	4.0366	4.0129	4.0257	4.0128	4.0008	4.0061	4.0017
VL	5.4815	5.2180	5.2495	5.1503	5.2136	5.1474	5.0025	5.2211	5.0146	5.1124
VF	6.8035	6.2711	6.1783	6.0177	6.0181	6.0270	6.0695	6.0184	6.0386	6.0618
V1	7.8883	7.7827	7.6826	7.5872	7.4960	7.4081	7.3232	7.2404	7.1594	7.0794
V2	8.9023	8.8066	8.7127	8.6202	8.5292	8.4392	8.3503	8.2620	8.1744	8.0871
V3	9.3509	9.1749	9.1365	9.0880	9.0624	9.0432	9.0298	9.0202	9.0130	9.0035
V4	10.4900	10.0395	10.1225	10.0680	10.0590	10.0435	10.0313	10.0263	10.0190	10.0198
V5	11.7967	11.6331	11.5013	11.3945	11.3074	11.2357	11.1758	11.1247	11.0798	11.0389
V6	12.8515	12.7212	12.6066	12.5049	12.4142	12.3324	12.2577	12.1886	12.1235	12.0611

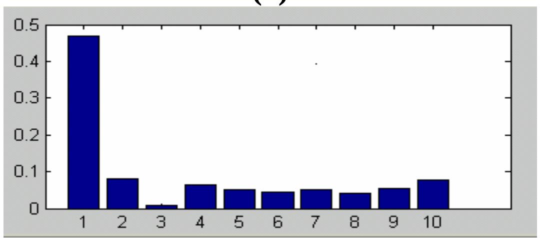
The measuring factor (accuracy) is computed for each diagnoses result. This factor equals the percentage of one minimum value of one lead divided by the average of the other same five values for the next selections to the same lead. This process is repeated to the next value in the same lead, and repeated to the next leads.

$$Accuracy = \frac{\min.value}{(sum\ of\ other\ \ five\ \ values)/5} * 100 \cdots \quad (1)$$

The accuracy results for each value of each lead from this equation are between (96.5487 % and 99.6704 %). Figure (2) shows an example for the lead II plotted as par plot.



(a)



(b)

Figure (2) a &b Coefficient of the LPC of lead II signal vector (Normal Case), where (b) is plotted as par plot.

5. Back Propagation Training Algorithm

In this section, the trainable layered neural networks will be studied, employing the input data. In the case of layered network training, the error can be propagated into hidden layers so that the output error information passes backward. The mechanism of the backward error transmission is used to modify the synaptic weights of internal and input layers. The back propagation algorithm is used throughout this paper for supervised training of multi-layer Feed-Forward Neural Networks (FFNN) [8, 12].

The back propagation designed to minimize the Mean Square Error (MSE) between the actual output of a multi-layer FFNN and the desired output.

The following steps give summery of back propagation algorithm:-

Step 1: $\eta > 0$, E_{max} chosen, where weights W and V are initialized at small random values: W is (k x J) and V is (J x I).

Step 2: Training step starts here, input is presented and layers outputs computed [*f(net)*]:

$$f(net) = \frac{2}{1+exp(-\lambda net)} - 1 \qquad ...(2)$$

$y_j \leftarrow f(v_j^t x)$, for j=1, 2,..., J

Where v_j is the j'th row of V weights, and

$o_k \leftarrow f(w_k^t y)$, for k = 1,2,...K Where w_k is the k'th row of W weights.

Step 3: Error value is computed:

$$E \leftarrow \frac{1}{2}(d_k - o_k)^2 + E, \qquad \text{for } k = 1, 2, ..., K$$

Step 4: Error signal vectors δ_o and δ_y of both layers are computed. Vector δ_o is (Kx1), and δ_y is (Jx1). The error signal terms of the output layer in this step are:

$$\delta_{ok} = \frac{1}{2}(d_k - o_k)(1 - o^2), \qquad \text{for } k = 1, 2, ..., K$$

The error signal terms of the hidden layer in this step are: $\delta_{yj} = \frac{1}{2}(1 - y_j^2)\sum_{k=1}^{K} \delta_{ok} w_{kj}$

for j=1, 2,…, J.

Step5: Output layer weights are adjusted:

$w_{kj} \leftarrow w_{kj} + \eta \delta_{ok} y_j$, for k=1, 2…, K and j=1, 2,…, J.

Step 6: Hidden layer weights are adjusted:

$v_{ji} \leftarrow v_{ji} + \eta \delta_{yj} x_i$ for j=1, 2,…, J and i=1, 2,…, I.

Step 7: Repeat by going to step 2.

Step 8: The training cycle is completed. for $E<E_{max}$ terminate the training session. If $E>E_{max}$, then $E \leftarrow 0$, and initiate the new training cycle by going to step 2.

6. Artificial Neural Networks Design and Computer Simulation Result

The major implementation in this paper is to design and learn the ANN as a diagnostic system. The manner in which the neurons of a neural network are structured is intimately linked with the learning algorithms used to train the network. The networks of ANN's are designed and optimized to operate as diagnosing machine as follows:

a) Two networks for primary diagnosis.

b) A network for giving the final diagnosis results.

c) ANN for Rhythm Diagnosis.

There are 30 hidden neurons used in the hidden layer for both ANNs. In general a series of training epoch equal about (97005) steps are used to approximate the final diagnosis networks as shown in figure (3). Figure (4) shows the Mean Square Error MSE

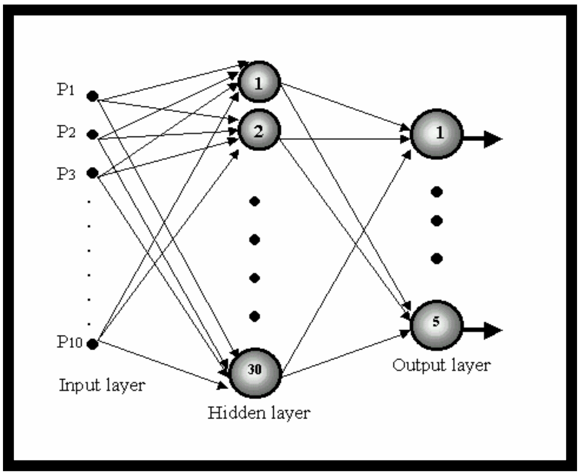


Figure (3) The neural network architecture for the first group.

The training parameters used are (α=0.45, γ=0.9) and the maximum number of iteration epoch-max is equal to (120000) are used. The same training steps were repeated twice for each one of the ANNs. First ANN to train on the leads (I, II, III, VR, VL, VF), and another ANN for leads (V1, V2, V3, V4, V5, V6).

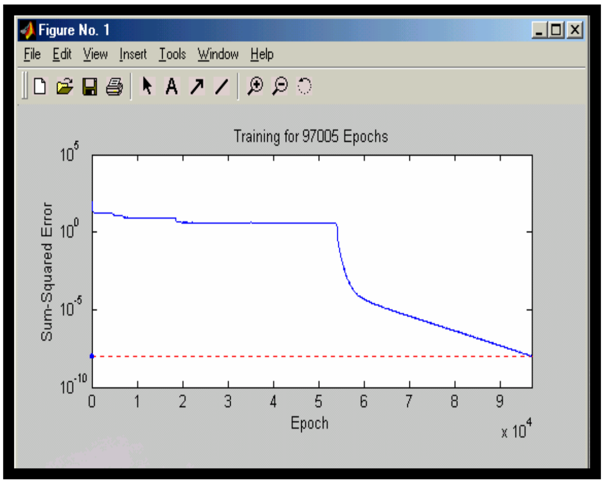


Figure (4) Sum square error of the first ANN output.

6.1 A Proposed Design of The NN for Final Diagnosis and Simulation Result

Final diagnosis results for all the12-lead ECG signals are done in this ANN. This design also trained by using multi-layer feed forward network (back-propagation learning algorithm). In this design the same five diseases should be classified (Normal, Angina, MI, RBBB, LBBB) in reference to all diagnosis of the 12-lead. The input is diagnosing output of the previous ANNs. The structure has 10 neurons in the input layer and one hidden layer of 30 neurons and one output layer of 5 neurons as shown in figure(5).

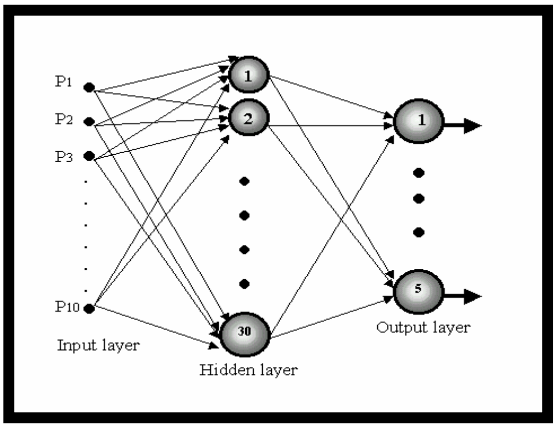


Figure (5) The neural network architecture for the final diagnosis.

By using 60000 training epochs, with tansig activation function for each layer, and training parameters (α=0.4, γ=0.9) ,the network became stable after (27274) training epochs. Figure (6) shows the sum of square errors of the final ANN.

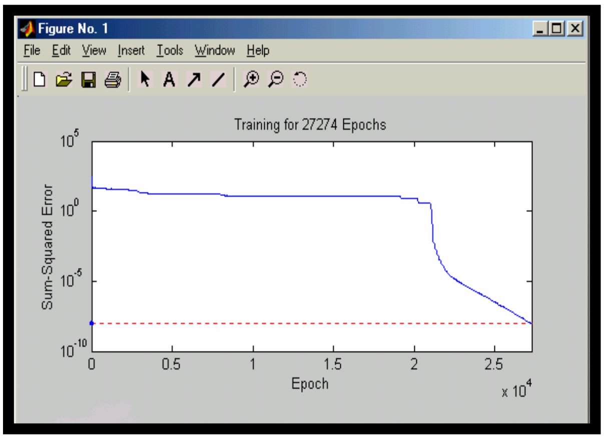


Figure (6) Sum square error of the final ANN output

6.2 ANN for Rhythm Diagnoses

This ANN is designed to operate as rhythm diagnoses, by using back-propagation algorithm with 12 input node and one hidden layer of 20 neurons together with one output layer of 4 neurons as shown in the figure (7).

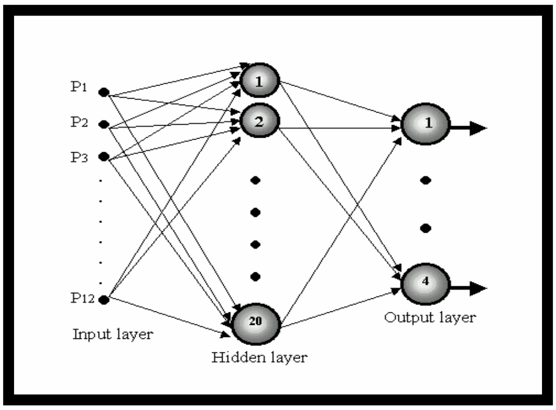


Figure (7) Architecture of the final ANN for rhythm diagnoses.

In this design four cases should be classified, these are (Normal, Disarhythma, Tachycardia, and Bradycardia). The classification strategy depends upon the signal period identification technique, in this technique the program will record location of the second peak (or bottom) of the lead signal under test and store this value in special matrix (1x12). This process is done for 12-lead. After completing these cases, the data matrix inters to the ANN and produce the results for this case. The design is stable with the training parameters are (α =0.4, γ =0.9), and tansig activation function for each neurons in the network, and after 595 training epochs. Figure(8) shows the final sum square error of the ANN.

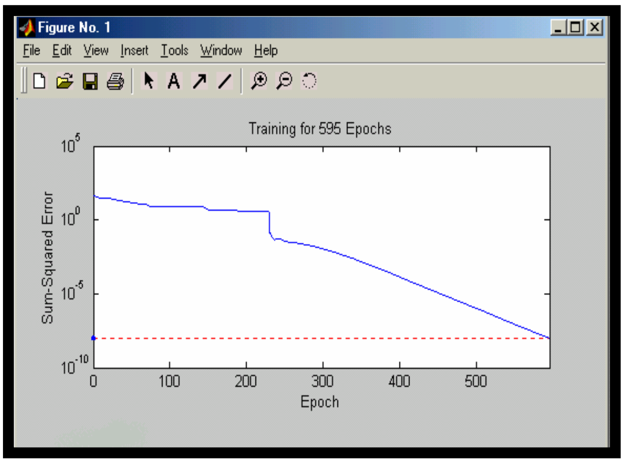


Figure (8) Sum square error of the final ANN for arhthm diagnoses.

7.Software Implementation and Diagnosing Results

In the beginning, the ECG image may be colored or not. In this program the ECG image is auto converted to a gray level. Figure(9) shows this image after being converted. Then by using mouse can be rectangular region of the lead image can be selected in order to be tested as shown in Figure(10). After selecting lead image, inter the number of this lead. Figure(11) shows this rectangular region of the lead image.

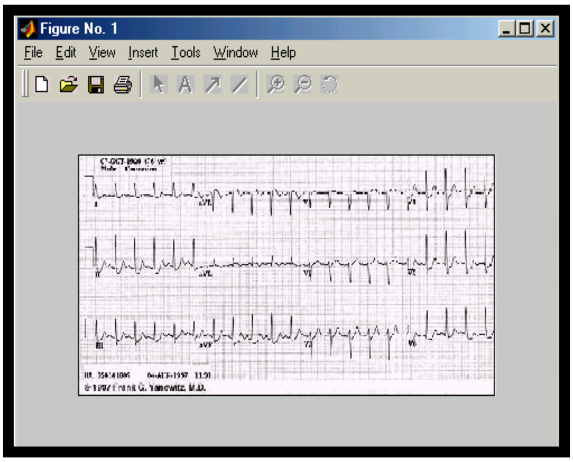


Figure (9) ECG image examples.

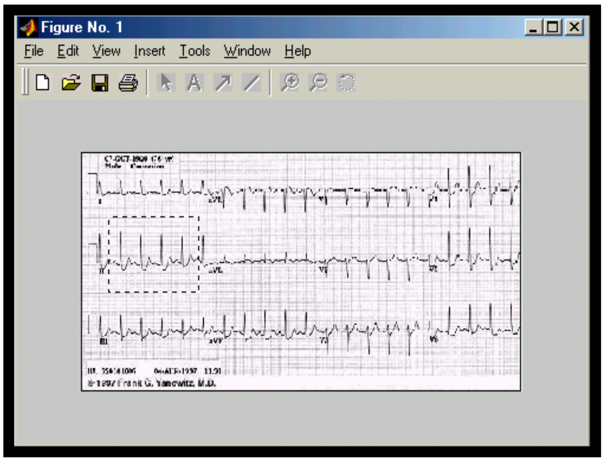


Figure (10) Lead selection operation

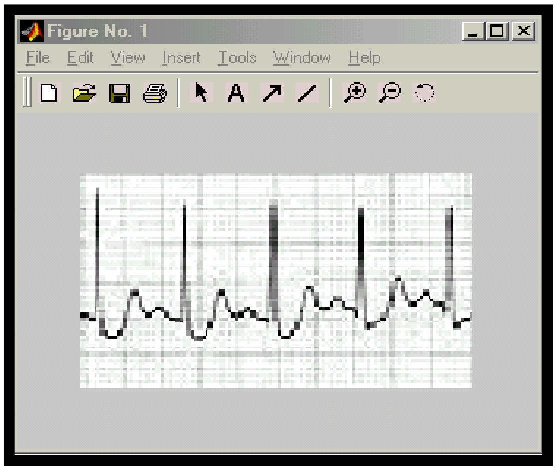


Figure (11) Selected rectangular lead region (lead II).

Can be Crop the selected lead signal image again to (6X10) large square, this second select is to fit all the lead images at the same size as shown in Figure(12).

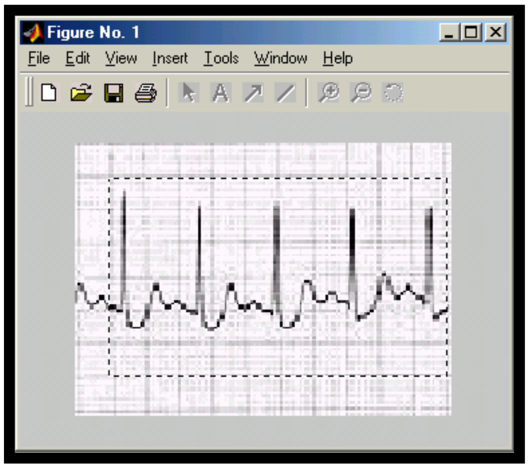


Figure (12) Crop lead II signal image to fit (6 X 10) large square.

In the same step the background of the lead image is removing by applying special filter, and allow to changing the characteristic for this filter, if the noise (as small points) is present with this selected lead image. Figure(13) and Figure(14) are shows this state after and before remove background.

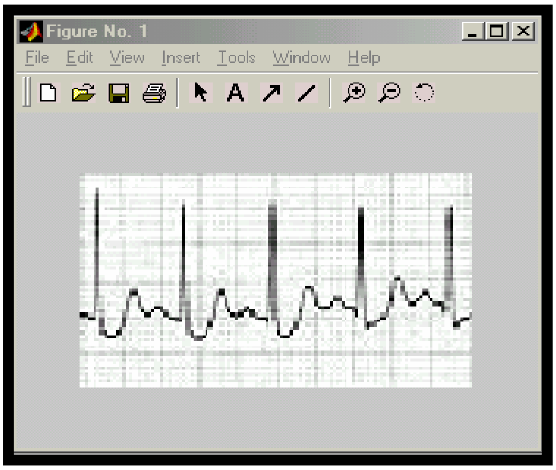


Figure (13) Lead after fit selection with its background.

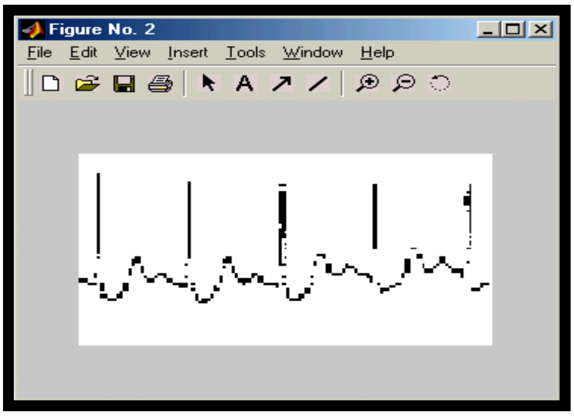


Figure (14) Lead II after remove background.

After appearing figure (14) on the monitor, a message appears telling the user for the lead image selected. If this filter is enough to remove all noise on this lead image, the answer on this question is YES or NO. When the answer is yes, the program continues to execution the next steps, and when the answer is no, the program returning to display figure (13) on the monitor allowing the user to change the characteristic for the filter and select the rectangular lead image again, and so on until ensure the image on the monitor is clear from any noise. Figure(15) shows the following message:-

" If this filter enough to remove all noise on this image YES NO".

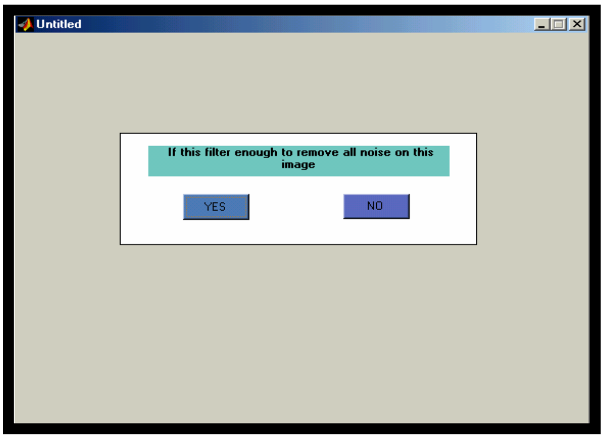


Figure (15) Message for the user.

After the lead image appears without any noise, the program will continue to execute the next step, and auto completes the slandering of the signal line. Figure (16) shows this signal line after complete slandering line.

From this signal the program will choose only one period, and this period is between two peaks (or bottoms), as shown in figure(17).

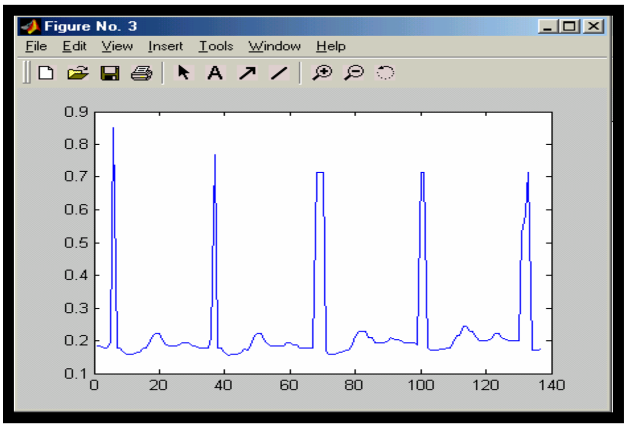


Figure (16) Slandering signal line.

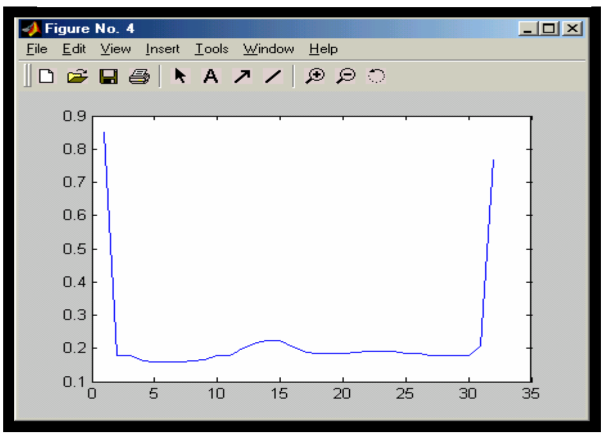


Figure (17) One period lead signal.

LPC is computed in order to input to the designed neural network. Figure (2) explores the LPC value for that lead signal. And the program will be returning to the first step in order to complete all ECG12-lead signals. Results from each lead signal are stored in two matrixes, one for first six leads (I, II, III, VR, VL, VF), and another to the second leads (V1, V2, V3, V4, V5, V6). Each matrix will be applied to one of the two ANNs to give primary diagnosis. An example for these data is mentioned in table (2). Figure (18) shows the output results of the final diagnosis of the ANN and the rhythm diagnosis.

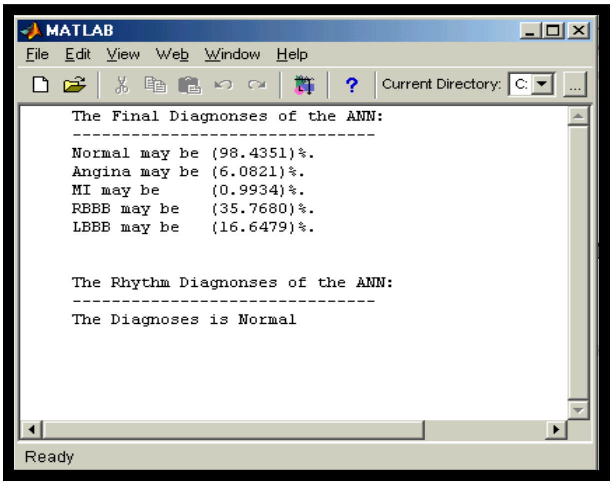


Figure (18) Final diagnoses results of the ANN and the rhythm diagnoses.

Finally figure (19) shows the main structure of the final system design.

8. ANN Test and Results

In order to test the performance of the ANN diagnosis, a new additional ECG record is used to test the performance of the ANN. These new ECGs are not previously used in the training operation. The testing operation are implemented by using 47 case studies, which unclouded 20 normal cases, 9 Angina pectoris cases, 8 MI cases, 6 RBBB cases, and 4 LBBB cases. These 47 cases were previously classified by an electocardiographer, and with the help of a Doctor. By using simple statistics, it is quite clear that the ANN classifications were true in 40 case, and it was wrong in 7 cases, that means the performance index of the ANNs is (40/47 *100) equals to (85%). The mismatch between the ANN decision and the electocardiographer in 7 cases can be characterized in different cases. Due to the uncertainty (poor reliability) of the primary classification of the electcardiographer for some of the complex cases which have interference with multi diseases. In some cases due to ECG recorded in short time, And in two cases due to error in the leads that are not attach with the body (poor connection with the body), or gelatin material was not used that helps the signal transform to the electrocardiographer.

9. Discussions and Conclusions

This work presents a method for automated detection of the heart patients using the 12-lead ECG. Each lead signal is decomposed using LPC and the resulting coefficients are used as inputs to ANN ensembles that are trained to detect the disease. The results obtained, show that the ANN can be trained by deferent cases. Such as use input data in series (providing the training data set for each lead) for the same network, and can be trained for more common disease with high accuracy by using greater input parameters. Also, high level of agreement between the ANN and the experienced electrocardiographer. Somehow, when there is obvious disagreement the ANN is correct somewhat more often than the expert, with regard to the constant standards of this trained ANN.

The networks that used in this work are in one hidden layer and use the pack-propagation training algorithm illustrated in section(5). Number of connections for each network, that used in the first group (first stag) are equal to product the number of input to the number of neurons in the hidden layer, (60 * 30 = 1800) connections. And the number of connections in the output layer in the same networks are equal to product the number of neurons in the hidden layer to the number of neurons in the output layer, (30 * 5 = 150) connections.

In this work, ANN can be designed to give high implementation in diagnoses, depending on how data pre-processing is done, and how these data applied as input to the ANN. For example, if the inputs to the

ANN consist of high and different numbers (divergent values), the training operations may be difficult and some of the neurons not learn these inputs, and by using LPC in pre-processing as compressed system in this work , the ANN can be training to these data in small size of neurons and short time.

It is possible to train any network for any data of any size. This can be done if follow the following steps. First choosing two or three patterns from the set of training patterns, these choose will be begun with the training operation to set all the required parameters at the optimum values. After complete training operation, the network is learned to these data. Secondly, adding one or two new patterns to these choosing data and starting with a new training operation until completing this training operation, and so on until complete all pattern sets. The advantage of this process is to hasty and to confirm the learning operation in smallest network with short time. Using large number of examples to train the ANN may be lead to lowering the risk of misdiagnosis, but some problems in preparing the suitable data references for this work.

It is very hard operation to collect a large number of suitable ECG records from different hospitals.

Use of LPC with ANN, gives the ANN the ability to be used in wide applications that consist of the signals, such as speech recognition, medical EEG interpretation, and weather interpretation.

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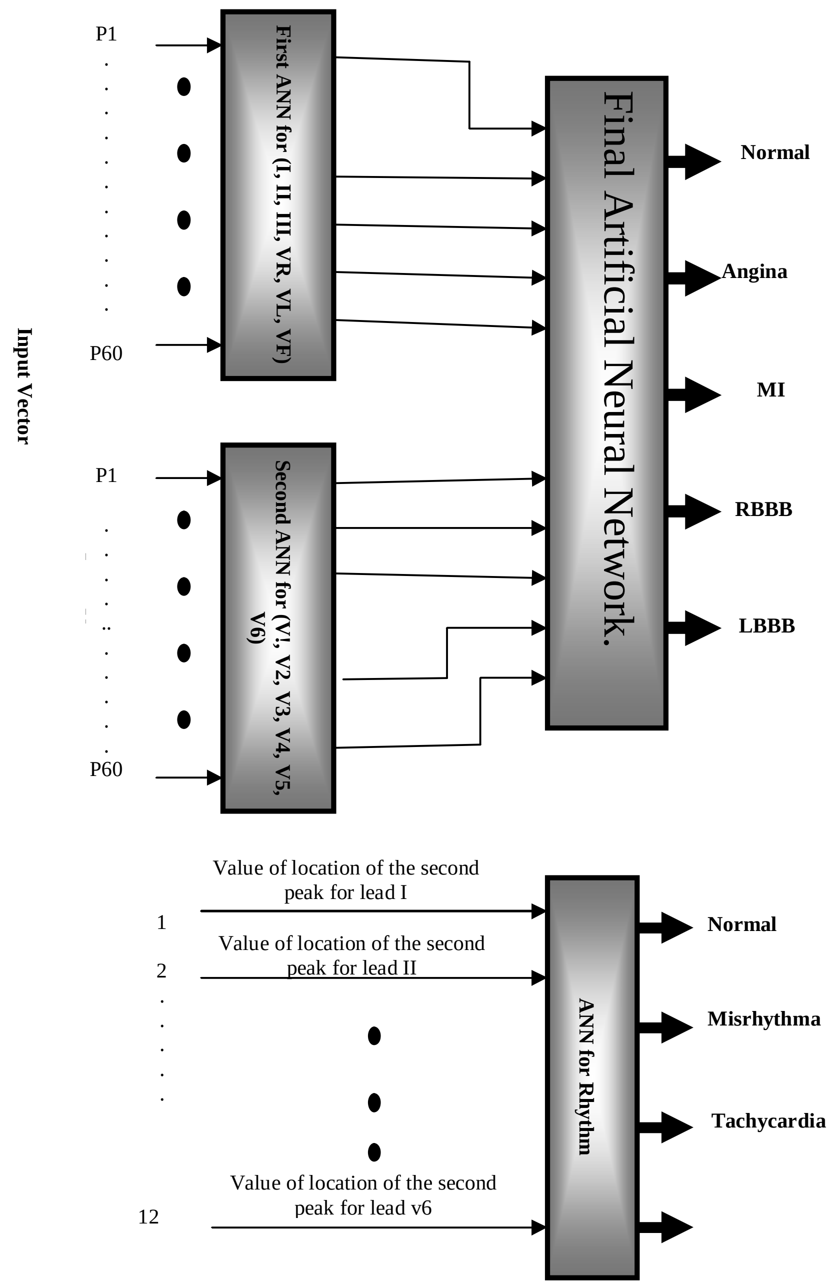

Figure (19) The main structure of the final ECG diagnoses.