DIAGNOSTIC MITRAL AND AORTIC STENOSIS BASED ON ARTIFICIAL NEURAL NETWORKS

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Abstract

For many centuries, one of the goals of humankind has been to develop machines, where the engineers and scientists are trying to develop intelligent machines. Artificial neural systems are present-day examples of such machines that have great potential to further improve the quality of our life.

Stethoscope is a tool that interpretation by a physician of heart sounds as a fundamental component in cardiac diagnosis. It is, however, a difficult skill to acquire. In this work, the presented study for a system intended to aid in heart sound classification based on artificial neural network (ANN).Where it is contain on three steps. The information acquire is the first step which included recording the heart sound from the patient by the sonoketle phone , where the sound heart can be heard and can record by small record instrument. The second step is analysis step, in which the sound wave file analyzed to get (11) parameter which represents the input to the third step (classification step). In classification step we can recognize the class which the sound wave files belongs to it. heart sounds of (64) subjects divided into two groups normal (20) subjects and heart valve diseases (44) subjects analysis and take times and frequencies as 11 node parameters that interred to input of network .The accurate result was obtained accurate classifier ($P<0.001$) with hidden node equal to 11, momentum and learning rate equal to 0.2, 0.7, 0.3 and 0.5 respectively with total error equal to 0.39.

Introduction

1. Stethoscope

Heart auscultation (the interpretation of sounds produced by the heart) is a fundamental tool in the diagnosis of heart disease. It is the most commonly used technique for screening and diagnosis in primary health care. In some circumstances, particularly in remote areas or developing countries, auscultation may be the only method available. However, detecting relevant symptoms and forming a diagnosis based on sounds heard through a stethoscope is a skill that can take years to acquire and refine. Because this skill is difficult to teach in a structured way, the majority of internal medicine and cardiology programs offer no such instruction [2].

It would be very advantageous if the benefits of auscultation could be obtained with a computer programs, using equipment that is low-cost, robust, and easy to use. The complex and highly no stationary nature of heart sound signals can make them challenging to analyze in an automated way. However, in this technological used have made extremely powerful digital signal processing techniques both widely accessible and practical. Local frequency analysis by using fast fourier transition FFT (local scale analysis) approaches are particularly applicable to problems of this type, and take these methods have been applied to study the correlation between these sounds and one valve diseases by ANNs[3].

Where in this work we combine local signal analysis methods with classification techniques to detect, characterize and interpret sounds corresponding to symptoms important for cardiac diagnosis. It is hoped that the results of this analysis may prove valuable in themselves as a diagnostic aid, and as input to more sophisticated method diagnosis systems [4].

2. Heart Valves

The heart consists of four chambers, two atria (upper chambers) and two ventricles (lower chambers). There is a valve through which blood passes before leaving each chamber of the heart. The valves prevent the backward flow of blood. These valves are actual flaps that are located on each end of the two ventricles (lower chambers of the heart). They act as one-way inlets of blood on one side of a ventricle and one-way outlets of blood on the other side of a ventricle. Each valve actually has three flaps, except the mitral valve, which has two flaps. The four heart valves are:

1-Tricuspid valve: located between the right atrium and the right ventricle

2-Pulmonary valve: located between the right ventricle and the pulmonary artery

3-Mitral valve: located between the left atrium and the left ventricle

4-Aortic valve: located between the left ventricle and the aorta [5].

3. Valvular heart disease

As the heart muscle contracts and relaxes, the valves open and shut, letting blood flow into the ventricles and atria at alternate times. The following is a step-by-step illustration of how the valves function normally in the left ventricle:

1. After the left ventricle completes its contraction phase, the aortic valve closes and the mitral valve opens, to allow blood to flow from the left atrium into the left ventricle.
2. as the left atrium contracts, more blood flows into the left ventricle.
3. When the left ventricle completes its contraction phase again, the mitral valve closes and the aortic valve opens, so blood flows into the aorta.

The job of a valve is to make sure that fluid flows only in the right direction. Your heart is a muscle which pumps blood around your lungs and the rest of your body. There are four valves in your heart. These valves guard the entrances and exits of the two pumping chambers in your heart (the two pumping chambers in your heart (the right and left ventricles). The valves at the entrances are there to make sure that the blood only goes into the ventricles. The valves at the exits only let blood out. A diseased or damaged valve can affect the flow of blood in two ways.

1. If the valve does not open fully, it will obstruct the flow of blood. This is called ‘valve stenosis’.
2. If the valve does not close properly, it will allow blood to leak backwards. This is called ‘valve incompetence’ or ‘regurgitation’.

Both stenosis and incompetence put an extra strain on the heart. If you have stenosis, the valve will obstruct the flow of blood, so your heart will have to pump harder to force the blood past the obstruction. If you have incompetence, a leaking valve will mean that your heart has to do extra work to pump the required volume of blood forwards. This is because your heart will be wasting energy as some of the blood is going backwards too.

3. The Perceptron Network

The perceptron was presented in 1958 by F.Rosenblatt in apsychological magazine. Originally it was a two-stage networks, in which the weight of the lower stage were constant and those of the upper stage could learn. Rosenblatt create this concept for the classification of visual patterns, which came from the human retina. Today, one mostly associates a single-stag, learning network with the term “perceptron”. The single-stage network has got many restrictions in their application area. Hence it becomes necessary to examine the features of multi-stage networks [5].

Multi-layer perceptron are feed-forward nets with one or more layers of nodes between the input and output node. These additional layers contain hidden units or nodes that are not directly connected to both the input and output nodes. Multi-layer perception overcome many of limitations of single-layer perception, but was generally not used in the past because effective training algorithms were not available. This was recently changed with the development of new training algorithm.

To use multi-layered networks efficiently, one needs a method to determine their synaptic efficacious and threshold potentials. A very successfully method, usually called error back-propagation was developed independently around (1985 by several research groups). It is based on generalization of gradient method.

The back-propagation learning method can be applied to any multi-layer network that uses differentiable activation function and supervised learning [6].

4.The learning Process

Multi layer perceptron always consist of at least three layers of neurons. As a result, the network will have an input layer, an output layer, and a middle layer(sometimes referred to as a hidden layer). [Computer program that learn].

Neurons communicate analog signals over the synaptic links. In general, all neurons in a layer are fully interconnected to neuron in adjacent layers. Information flows unidirectional from input through hidden and output layers. However, it flows in the reverse direction during training. Associated with each synapse a weight v_{ik} connecting input neuron $_i$ to hidden neuron $_k$, and a weight w_{kj} connecting hidden neuron $_k$ to output neuron .

Where $_j$ is an index over output units (with in a training pair).

Each neuron cell receives a net signal, which is the linear weighted sum of all its inputs. A logistic activation output function $1/(1+e^{-x})$ converts this to a smooth approximation to the classic step neuron of

McCullah and Pitts. The output h_k of hidden neuron $_k$ is given by

$$h_k = 1/(1+e^{-\Sigma viksi}) \qquad (1)$$

Similarly, the activation u_j of output neuron $_j$ is given by

$$U_j=1/(1+e^{-\Sigma wkj\ hk}) \qquad (2)$$

Since network weights are initially undetermined, a training process is needed to set their value. Back propagation refers to an iterative training process in which an output error signal is propagated back through the network and is used to modify weight values. The mean square error in case C is

$$E_C=½\Sigma(t_j-u_j) \qquad (3)$$

Where the summation is performed over all output nodes $_j$, and t_j is the desired or target value of output u_j for a given input pattern.

Training is begun by presenting a sample pattern to the sensor inputs of a network primed with random initial weights. The error of an output neuron, δ_j is defined by

$$\delta_j=u_j(1-u_j)(t_j-u_j) \qquad (4)$$

Weights w_{kj} are changed according to

$$\Delta w_{kj}(n)=\eta\delta_j h_k \qquad (5)$$

The constant η in the weight-adjustment equation is the learning rate. Its value (commonly between 0.25 and 0.75) is chosen by the neural network user, and usually reflects the rate of learning of the network. Values that are very large can lead to instability in the network, and unsatisfactory learning. Values that are too small can lead to excessively slow learning. Sometimes the learning rate is varied in an attempt to produce more efficient learning of the network; for example, allowing the value of η to begin at a high value and to decrease during the learning session can sometimes produce better learning performance. Usually a momentum term is included to improve the convergence, which determines the effect of previous weight change on present changes in the weight space. The weight change after n^{th} iteration is δ

$$\Delta w_{kj}\ (n)= \eta\delta_j h_k + \alpha\Delta w_{kj}\ (n-1) \qquad (6)$$

Where α is the momentum term and lies between 0 and 1.

After computing δj in the output layer, the error of neurons δ^*_k is defined by. For a hidden neuron, the rule changes to

$$\delta^*_k = h_k(1-h_k)\sum \delta_j w_{kj} \qquad (7)$$

Where h_k is the activation of hidden neuron k and summation is over the j neurons in the output layer. The weight correction for v_{ik} is similarly,

$$\Delta v_{ik}(n)= \eta\delta^*k\ s_i + \alpha\Delta v_{ik}(n-1) \qquad (8)$$

The total error in the performance of the network with particular set of weight can be computed by comparing the actual y, and the desired, d, output patterns for every case. The total error, E, is define by

$$E=\sum cEc \qquad (9)$$

Where (c) is an index over all of input-output pairs on training set and local error

$$Ec = ½ \sum(t_j u_j)^2 \qquad (10)$$

Before starting the training process, all of the weights must be initialized to small random numbers, these ensure that the network is not saturated by large values of the weights, and prevents certain other training pathologies. For example if the weights all start at equal value, and the desired performance requires unequal value, the network will not learn. After training is stopped, the performance requires of the network is tested [8] and [9].

Materiel and Method

The system for heart sound classification which was used in this project is shown in Fig.(1) which is consisted of the following component [6].

Fig.( ): Simple Heart Sound Classification System.

1.Information acquire step

This step is started when the patient be lied on the supine position, the sonokette probe first connected to the patient chest and then a gel is put on the proper location where heart sound is heard and can recorded by small recorded instrument and transmitted from the analog to digital (sound wave file) in order to fed to the computer by sound recorder software.

The sound wave files were divided into three classes according to our study requirement and they were investigated with the (echo cardiograph) echo C.G. The class are:

A-control class

The control class involves from many normal persons in both sexes, they had no history of heart disease.

B-Mitral stenosis class

This class contains many patients who had mitral stenosis disease where the mitral valve opening indicates that the tips of leaflets are restricted in their ability to open can be detected with echocardiographic examination and no had any complication heart diseases.

C-Aortic stenosis class

This class contains many patients who had aortic stenosis disease where the aortic valve opening indicates that the tips of leaflets are restricted in their ability to open can be detected with echocardiographic examination and had no any complication heart diseases.

2. The analysis step

2.1 sound wave:-

The two major sounds heard in the normal heart sound like “ lub dub”. The “ lub” is the first heart sound , commonly termed S1 , and is caused by turbulence caused by the closure of mitral and tricuspid valves at the start of systole. The second sound, “dub” or S2, is caused by the closure of aortic and pulmonic valves, marking the end of the systole. Thus the time period elapsing between the first heart sound and second sound defines systole (ventricular ejection) and the time between the second sound and the following first sound defines diastole (ventricular filling).

2.2. Parameter

The parameters in this step divided into two types according to the requirements of this study which are:-

First. Measured Parameters

Which includes all the parameters which are taken directed from the signal (include time component in second) and its

A-systolic heart sound time (T1)

Begins with or after the first heart sound (S1) and ends at or before the subsequent second heart sound (S2).

B- Diastolic heart sound time (T2) begins with or after the second heart sound and ends before the subsequent first heart sound.

Also, the parameters can be classified according to their time of on set as

1. Mid-systolic murmurs time (T12)

Midsystolic murmurs occur in several setting such as the aortic valve stenosis, its began after the first heart sound (S1) , rises in crescendo as flow diminishes, ending just before the second heart sound (S2).

2. Early systolic murmurs time (T11)

Murmurs confined to early systole begin with first heart sound, diminish in decrescendo, and end well before the second heart sound midsystolic murmurs, generally at or before mid-systole, certain type of mitral regurgitation

3. Late systolic murmurs time (T13)

The term “late systolic “applies when a murmur begins in mid-to-late systole and proceeds up to the second heart sound.

B-Diastolic Heart Sound Time (T_2)

1. Early diastolic murmurs time (T21)

It's represented by aortic regurgitation; the murmur begins with the aortic component of Second heart sound and end well before mid-diastolic heart sound is begins.

2. Mid-diastolic murmurs time (T22)

A mid-diastolic murmur begins at clear interval after the second heart sound, the majority of it originate across mitral or tricuspid values during the rapid filling phase of the cardiac cycle its represented by mitral stenosis

3. Late-diastolic murmurs time (T23)

It occurs immediately before the first heart sound where this murmur originate at the mitral or tricuspid orifice because abnormal pattern of these values.

Second. Calculated and Statistical Analysis

After calculating the results (which includes all the parameters taken from frequency domain and calculate the calculated parameters which are:-

A. Median (M)

This value that occurs in the middle of a set of values the values are arranged in increasing magnitude.

B. Confidence Intervals (CI)

Can be found from the following formula

Mean $\pm$ t_c (standard deviation / (Sqr(N-1))

Where t_c represented to the tabulated constant and for 95% confidence intervals equal to 2.26 and N represented to the number of subjects.

These are tabulated. The data of all subjects show the mean and standard deviation, in order to highlight upon the magnitude of variability of constituent units of input neural parameters of heart valves function for normal persons with the parameters of the other relative groups. Then the rate difference from control (I %) is calculated together with the t-test (the comparison between the mean values four each two groups tested by unpaired students t-test).

Besides that, the percentage difference between females and males (II %) for each group is calculated as well as their t-test (the comparison between the mean values for each one group tested by paired students t-test).

Also, P value less than 0.05 was considered to be significant (*). P value less than 0.01 was considered to be high significant (**).

3. classification step

In this step a single multi layer artificial neural network is used. The output of the analysis step represents the input to classification step (11 parameter) and the number of nodes in the input layer equals to the number of input parameters (11 node) which is the number of hidden layer. In this work, a variable number is used and it is found the best result (obtained with 11 node), the output layer represented by three node corresponding to the number of classes. The binary code is used to represent the class; and refer to the class 1 by 000, class 2 by 001, and class 3 by 011 as shown in Fig.(2).

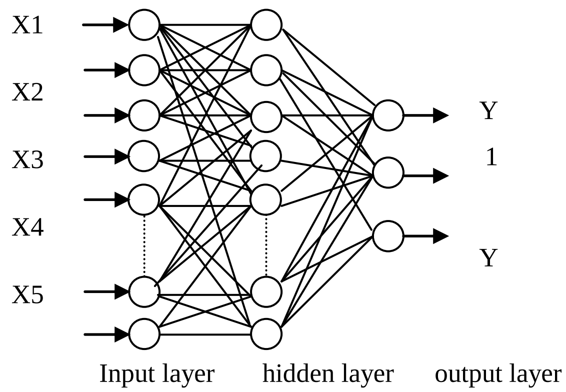

Fig. (2) : ANN With Input Layer, Hidden Layer and Output Layer (where input layer represented to the input data that be enter in to the ANN, hidden layer: - The arrangement the pass of date inside the ANN, output layer:-The final result of ANN)[10].

Results

Analysis and calculations were made for all sound wave recorded in order to establish the variability of constituent units for the function of the heart valves by the sound wave parameters of normal persons and the other relative groups parameters.

1. Patients Collection Analysis

The present study included (64) subjects of which (33) were males and (31) were females; cases were divided in two groups:

1.1. Group I (Control Group)

This group included (20) normal subjects, of which (10) were males which forms 50% of the total group. The mean male age was (32.7±8.9) years and their body mass index was (20±5.2) kg/m^2.Females subjects were (10), which forms 50% of the total group. The mean of female age was (42±9.2) years and their body mass index was (18.1±5.08)kg/m^2 Table (4).

1.2. Group II (Valvular Heart Diseases)

Aortic Stenosis (AS)

This group included (10) Aortic Stenosis patients, of which (5) were males which forms about 50% of the total number. The mean of male age was (25.7±9) years, their body mass index were (20.2±9)kg/m^2.The number of female subjects (5), which forms 50% of the total number. The mean of female age was (29.7±11) years and their body mass index was (19.9±7.6) kg/m^2 Table (5).

Mitral Stenosis (MS)

This group included (8) Mitral Stenosis patients, of which (4) were males which forms about 50% of the total number .The mean of male age was (27.6±6.6) years , their body mass index was (19.4±9) kg/m^2.The number of female subjects (4),which forms 50% of the total number. The mean of female age was (30.4±12.6) years and their body mass index was (20.6±7.9) kg/m^2 Table (6).

Murmurs

A. Aortic Valve Diseases

2. Aortic Stenosis Murmur

We calculated the values of median and confidence interval of frequency domain for mid-systolic murmur, also measured times between and in murmur itself. Murmur placed in second third of systolic time as shown in Table (5).

B. Mitral valve diseases

2. Mitral Stenosis Murmur

We calculated the values of median and confidence interval of frequency domain for mid-diastolic murmur, also measured times of murmur and among it. Murmur placed in second third of diastolic time as shown in Table (6).

The murmur measured values of times T_{11}, T_{12}, T_{13}, T_{21}, T_{22} and T_{23} were measured between and in murmur itself for all the diseases groups (group II) as shown in Table (6).

The first three times represent to the times among the murmur in diastolic period of time and the others times represent to the times among the murmur in systolic period of time.

Patient Heart Sound Form

These are the forms which have been specially prepared to record much information and measurements taking from patient directly and which includes patients name, address, age and sex.

1. Normal heart sound signal

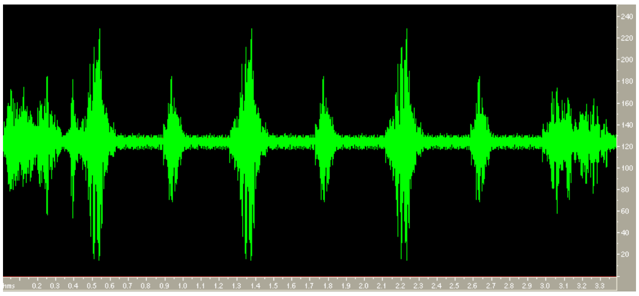

Fig.(3) : Normal heart sound wave.

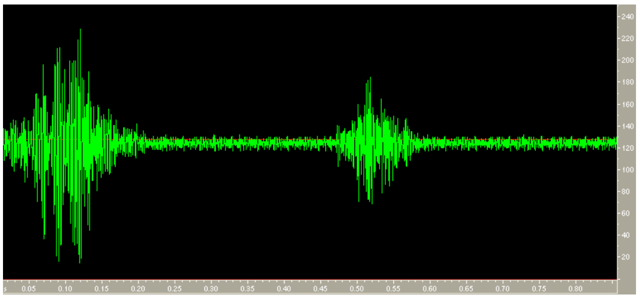

Fig.(4) : One signal taken from normal heart sound wave to get analysis.

Table (1)
The parameters analysis of the wave in Fig. (4)

T21	T2	T13	T12	T11	T1
0	0.31	٠	0	0	0.23
CI -	CI +	Medain s3	T23	T22	
0	0	0	0	0	

2. Abnormal heart sound signal

There are two types of wave represents two types of valvular heart diseases according to our study requirements

A.Aortic stenosis wave

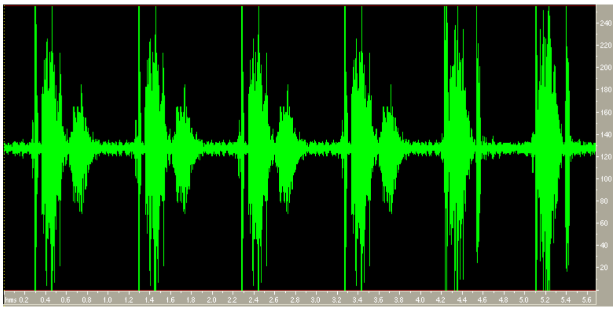

Fig . (5) : Aortic stenosis wave.

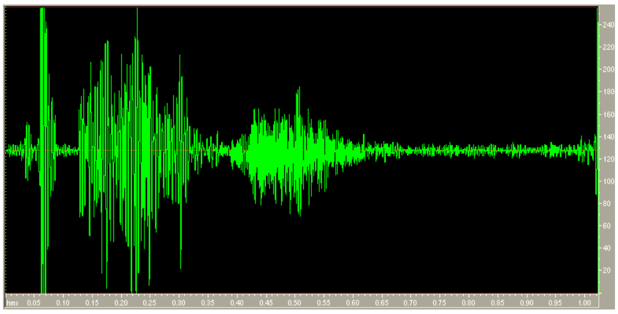

***Fig.(6)* : One signal taken from *Aortic stenosis wave* to get analysis.**

Table (2)
The parameters analysis of this wave in Fig. (5).

T21	T2	T13	T12(M)	T11	T1
0	0.38	0.05	0.2	0.05	0
CI -	CI +	Medain s3	T23	T22	
-0.1865	0.2021	0.0722	0	0	

B.Mitral stenosis waves

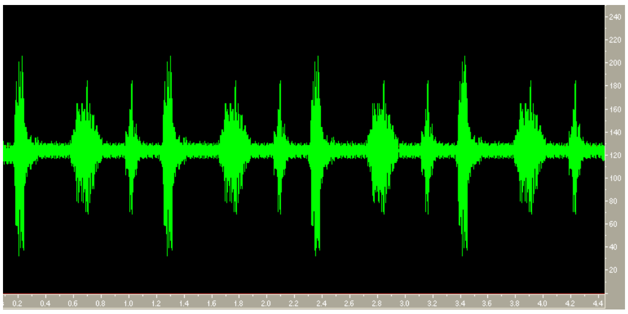

Fig.(7) : Mitral stenosis wave.

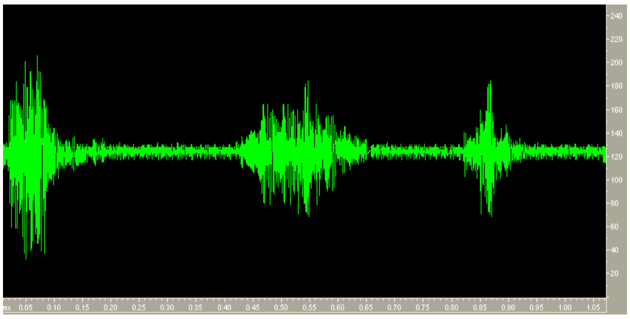

***Fig.(8)* : One signal taken from Mitral stenosis *wave* to get analysis.**

Table (3)
The parameters analysis of this wave in Fig.(8).

T21	T2	T13	T12	T11	T1
0.167	0	0	0	0	0.296
CI -	CI +	Medain s3	T23	T22(M)	
-0.0405	0.1031	0.0345	0.144	0.116	

Therefore, the studied parameters can be tabulated of all subjects' waves for each group of disease as shown in below

1. Normal waves parameters

Table .(4)
Normal waves parameters.

wave no.	T1	T11	T12	T13	T2	T21	T22	T23	Medain s3	CI +	CI -
1	0.26	0	0	0	0.33	0	0	0	0	0	0
2	0.23	0	0	0	0.32	0	0	0	0	0	0
3	0.25	0	0	0	0.3	0	0	0	0	0	0
4	0.26	0	0	0	0.31	0	0	0	0	0	0
5	0.32	0	0	0	0.28	0	0	0	0	0	0
6	0.22	0	0	0	0.32	0	0	0	0	0	0
7	0.25	0	0	0	0.55	0	0	0	0	0	0
8	0.24	0	0	0	0.38	0	0	0	0	0	0
9	0.3	0	0	0	0.3	0	0	0	0	0	0
10	0.26	0	0	0	0.31	0	0	0	0	0	0
11	0.275	0	0	0	0.31	0	0	0	0	0	0
12	0.275	0	0	0	0.28	0	0	0	0	0	0
13	0.22	0	0	0	0.29	0	0	0	0	0	0
14	0.21	0	0	0	0.28	0	0	0	0	0	0
15	0.25	0	0	0	0.29	0	0	0	0	0	0
16	0.22	0	0	0	0.29	0	0	0	0	0	0
17	0.24	0	0	0	0.3	0	0	0	0	0	0
18	0.28	0	0	0	0.33	0	0	0	0	0	0
19	0.3	0	0	0	0.31	0	0	0	0	0	0
20	0.23	0	0	0	0.31	0	0	0	0	0	0

2. Aortic stenosis waves parameters

Table (5)
Aortic stenosis waves parameters.

wave no.	T1	T11	T12(M)	T13	T2	T21	T22	T23	Medain s3	CI +	CI -
1	0	0.05	0.2	0.05	0.38	0	0	0	0.0722	0.202	-0.1865
2	0	0.06	0.22	0.06	0.39	0	0	0	0.0065	0.027	-0.0271
3	0	0.04	0.18	0.04	0.39	0	0	0	0.0316	0.121	-0.0271
4	0	0.04	0.19	0.04	0.34	0	0	0	0.0283	0.079	-0.0632
5	0	0.045	0.21	0.05	0.42	0	0	0	0.2985	0.536	-0.5359
6	0	0.043	0.19	0.03	0.298	0	0	0	0.0215	0.11	-0.0476
7	0	0.052	0.2	0.04	0.272	0	0	0	0.0094	0.036	-0.0048
8	0	0.057	0.2	0.04	0.309	0	0	0	0.0185	0.053	-0.0372

3. Mitral stenosis waves parameters

Table (6)
Mitral stenosis waves parameters.

wave no.	T1	T11	T12	T13	T2	T21	T22(M)	T23	Medain s3	CI +	CI -
١	0.45	0	0	0	0	0	0.16	0.3	0.006	0.082	-0.05
٢	0.31	0	0	0	0	0	0.206	0.2	0.021	0.129	-0.02
٣	0.384	0	0	0	0	0	0.103	0.3	0.023	0.056	-0.04
٤	0.224	0	0	0	0	0	0.155	0.1	0.024	0.107	-0.03
٥	0.241	0	0	0	0	0	0.105	0.2	0.015	0.151	-0.04
٦	0.296	0	0	0	0	0	0.116	0.1	0.035	0.103	-0.04
٧	0.315	0	0	0	0	0	0.08	0.2	0.002	0.155	-0.08
٨	0.293	0	0	0	0	0	0.215	0.1	0.01		-0.04
٩	0.226	0	0	0	0	0	0.294	0.1	0.057	0.19	-0.11

Discussion

Cardiac auscultation continues to be the heath are professionals primary tool for distinguishing between innocent and pathological heart murmurs in valvular heart diseases .The sound of heart lesions have been previously described. For medical persons to acquire high-quality auscultation skills requires the guidance of an experienced instructor using a sizable number of patients along with frequently practice. Unfortunately, the interpretation of auscultation finding is prone to error [11].

In this research the suggesting system was evaluated using heart sounds corresponding to different heart conditions: normal, mitral valve stenosis and aorta valve stenosis. The classifier was trained using a single heartbeat cycle from each wave. The analysis of these waves were used to provide these parameters represented to all these waves of sound and the extracted parameters from sound wave file refer to as a times of diastole period, systole period and both first and second heart sound waves, also with values of concerning first and second heart sound after calculated both median and confidence interval for frequency domain of these waves. Because there were no significant difference between these parameters in these groups (group I and group II) as shown in Tables (5, 6).

A new parameters can be add such as times in and among murmur T_1, T_{11}, T_{12}, T_{13}, T_2, T_{21}, T_{22} and T_{23}, also values of concerning murmur after calculated both median ,and confidence interval for frequency domain as shown in Tables (5,6).

The network must learn decision surfaces from a set of training patterns so that these training patterns are classified correctly, then after training, the network must also be able to generalize, such as correctly classify test patterns it has never seen before. The data set comprised 64 examples, recorded from 44 patients, 36 examples used as training set and the remaining used as test set.

The learning requires the entire each input parameters Table (4), with a target vector representing the desired output, together these are called a training parameters [12]. Usually network is trained over a number of such training set parameters, called a training set [13]. An input vector is applied, the output of the network is computed and compared to the corresponding target vector and the difference (error) is fed back through the network and weights are changed according to an algorithm that tends to minimize the error [14]. The vectors of the training set are applied sequentially and errors are computed and weights adjusted for each vector, until the total error for the entire training set is at acceptably low level where reach in to (0.39).

The results of training and testing of ANN is performed the classifier system (mapping) to become ready for classified wide range of heart valvular diseases [15].

Conclusion

An ANN classifier was constructed for the task of discriminating among normal, systolic and diastolic heart sound .The data set comprised 64 examples, recorded from 44 patient, 36 examples used as training set and the remaining used as test set. The extracted parameters from sound wave file refer to as (T1,T2,T11,T12,T13,T21,T22,T23,M,C+,C-).

Accurate classifier is obtained with hidden node equal to 11, momentum and learning rate equal to 0.2, 0.7, 0.3 and 0.5 respectively with total error equal to 0.39.

Fig.(9) illustrated the mean square error (total error) decrease when the number of epoch is increase and this is a natural result because when the epoch is increase from ($5X10^5$) to the ($2X10^6$) the number of network training are increase and the network map became more efficiency to classification heart sound waves [6].

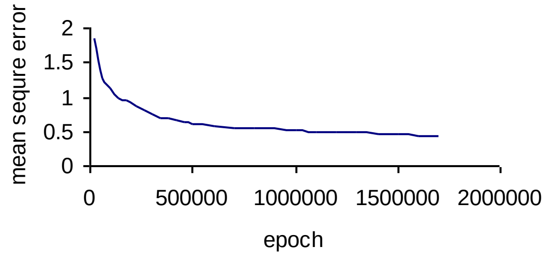

Fig.(9)relationshap betw een mean sequire error and number of epoch.

Fig. (9) : Relationship between mean squire error and number of epoch.

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الخلاصة

بقي تطوير الالة واحدة من الاهداف التي سعى اليها الانسان على مر العصور، حيث قام المهندسون والعلماء بمحاولة تطوير الالات الذكية فنظم الشبكات العصبية تعتبر مثال لهذة الالات التي رفدت التقدم الحاصل في حياتنا اليومية.

سماعة الطبيب تعتبر وسيلة تمكن الاطباء من سماع صوت القلب كمرحلة اساسية من مراحل تشخيص القلب لذلك ففي هذا البحث صممت طريقة لتصنيف أصوات القلب بواسطة الشبكات العصبية التي تتضمن ثلاث مراحل. ففي المرحلة الاولى يتم تسجيل صوت القلب من المريض مباشرة بواسطة السونوكيت والمرحلة الثانية تحليل الصوت الى (١١) متغير تعتبر كمدخلات في الشبكة العصبية التي تصنف هذة المتغيرات كمرحلة ثالثة.

الغاية من البحث أيجاد منظومة تستطيع تشخيص اصوات القلب بنسبة خطأ قليلة لذلك فقد اخذت اصوات (٦٤)عينة قسمت الى مجموعتين المجموعة الطبيعية(٢٠) عينة ومجموعة امراض الصمامات القلبية(٤٤) عينة ،حلل كل صوت الى احد عشر متغير للزمن والتردد اعتبرت كمدخلات للشبكة العصبية.

النتيجة النهائية كانت الحصول تصنيف اصوات القلب بصورة دقيقة($P<0.001$) بـ ١١ عقدة خفية بمعدل تعلم تساوي 0.5, 0.2,0.7,0.3 ونسبة خطأ تساوي 0.39 .