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Heart Murmur Detection using Artificial Neural Network

كشف اصوات القلب بأستخدام الشبكات العصبية الاصطناعية

A Thesis Submitted in Partial Fulfillment of The Requirements of the degree awards of MSc. In Biomedical Engineering

By

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Dedication

Dedicated to family

Acknowledgements

I would like to thank the Department of Bio medical Engineering at the Sudan University for providing me opportunity to research. I am also thankful to the University of sudan for the support in my research and experimentations. I want to extend my gratitude towards the very helpful and supportive teachers namely Walla Houssen.

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Last but not the least, I want thank my advisor and mentor Dr.Eltahir Mohamed Hussein for his continuous guidance throughout the project and without which I would not be able to finish this research.

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Abbreviations

A I : Artificial Inelegant

ANN: Artificial Neural Network

FFBP: Feed- Forward Back Propagation

LMS : least Mean Square

MLP : Multi Layer Perceptron

PDA : Patient Ductusarteriosus

MSE : Mean Square Error

Abstract

Accurate detection and classification of pathological heart murmurs by auscultation has been a challenge for physicians for a long time. In this research, we have used a AI techniques rely on converting the heart sounds to electrical signals and processing those signals by matlab tool box for murmur detection and classification. We have designed a heart murmur detection system based upon this approach and have tested this system using simulated heart sounds of various murmur types. Our test results show that the used of multilayer perceptron ANNs improve heart murmur detection accuracy up to (97%).

المستخلص

الكشف الدقيق وتصنيف اصوات القلب المرضيه عن طريق الاستماع كان يمثل تحديا كبيرا للاطباء لفترة طويله . في هذا البحث استخدمت تقنية الزكاء الاصطناعي والشبكات العصبيه الاصطناعيه لتحويل اصوات القلب الي اشارة كهربائيه وعولجت هذه الاشارة بواسطه الماتلاب .

تم تطبيق هذه التقنية لاكتشاف الاصوات الطبيعيه والغير طبيعيه واستخدمت شبكتين وقورنت بين النتائج , واستخدمت لاختبار النظام مجموعة مختلفه من الاصوات الغير طبيعيه ونتيجة الاختبارات ادت الي ان استخدام الشبكة متعددة الطبقات تعطي نتائج افضل واكثر دقه بنسبة تصل الي (97%) .

Chapter One

Introduction

1.1 General View

The incidence of heart murmurs in the patient's population is reportedly as high as 77% to 95%. However, <1% of this population has heart disease.[1] Early recognition is an important goal [2], and equally important is avoiding misdiagnosing a pathological heart murmur in a healthy people without heart disease. To acquire high-quality auscultation skills requires the guidance of an experienced instructor using a sizable number of patients along with frequent practice. Unfortunately, the interpretation of auscultation findings overall remains prone to error [3,4-6] . Imaging technologies can provide more direct evidence of heart disease; however, they are generally more costly. Efforts to develop an inexpensive screening device that can assist in the differentiation between innocent and pathological heart murmurs have met with limited success [7].

There has been much excitement in the scientific literature in recent years regarding artificial neural networks (ANNs) [9,8] in medicine[10] and, specifically, in cardiology applications [11, 12]. ANNs are valuable tools used in complex pattern recognition and classification tasks. They learn complex interactions among inputs and identify relations in input data that may not be apparent to human analysis [14]. The most common type of ANN consists of 3 layers of processing units: the input layer, the hidden layer, and the output layer connected in sequence.

1.2 Problem statement:

Unfortunately, the interpretation of auscultation findings overall remains prone to error Imaging technologies can provide more direct evidence of heart disease; however, they are generally more costly. Efforts to develop an inexpensive screening device that can assist in the differentiation between innocent and pathological heart murmurs have met with limited success.[2]

1.3 Objectives of this research

The objectives of this research are to:

1. Early recognize of heart disease in patients.
2. Avoid misdiagnosing a pathological heart murmur in a healthy people without heart disease.

1.4 Methodology

1. To Analysis heart sounds using ANNS to record number of patients (pathological and innocent murmurs).
2. Sound samples were processed using digital signal analysis and fed into a Feed Forward Back Propagation (FFBP) and Malty Layer Perceptron.

1.5 Theoretical foundation

Many research efforts have been made to apply artificial intelligence (AI) for rigorous detection/classification of heart murmurs but reported success rates have been low. All of the current AI techniques rely on converting the heart sounds to electrical signals and processing those signals via electronic circuitry of AI for murmur detection and classification. In this research, we have used a novel approach to pre-process the electrical heart sound signals by altering the electrical signal in a similar way as is done by human cochlea before they go to AI for murmur detection/classification. Cochlea-like pre-processing changes the spectral contents of the heart sound signal to enhance the murmur information which can then be detected and classified more accurately by AI circuitry.We have designed a heart murmur detection/classification system based upon this approach and have tested this system using simulated heart sounds of various murmur types. Our test results show that this approach significantly improves heart murmur detection/classification accuracy.[15] , diagnostic system based on Artificial Neural Networks (ANN) is implemented as a detector and classifier of heart murmurs. Segmentation and alignment algorithms serve as important pre-processing steps before heart sounds are applied to the ANN structure. The system enables users to create a classifier that can be trained to detect virtually any desired target set of heart sounds. The output of the system is the classification of the sound as either normal or a type of heart murmur. Testing has been conducted using both simulated and recorded patient heart sounds. Results are described for a system designed to classify heart sounds as normal, aortic stenos is, or aortic regurgitation. The system is able to classify with up to 85+- 7.4% accuracy and 95 +- 6.8% sensitivity for a group of 72 simulated heart sounds. [16], In this paper we present the implementation of a diagnostic system based on artificial neural networks (ANN) that can be used in the detection and classification of heart murmurs. The system enables users to create a classifier that can be trained to detect virtually any desired target set of heart sounds. The ultimate goal of this research is to implement a heart sounds diagnostic system that can be used to help physicians in the auscultation of patients and to reduce the number of unnecessary echocardiograms - those that are ordered for healthy patients. Testing has been conducted using both simulated and recorded patient heart sounds as input. Three sets of results for the tested system are included herein, corresponding to three different target sets of simulated heart sounds. The system is able to classify with up to 85 plusmn 7.4% accuracy and 95 plusmn 6.8% sensitivity. For each target set, the accuracy rate of the ANN system is compared to the accuracy rate of a group of 2nd year medical students who were asked to classify heart sounds from the same group of heart sounds classified by the ANN system.[17],the purpose of this research is to address the lack of effectively accurate cardiac auscultation present at the primary care physician office by development of an algorithm capable of operating within the hectic environment of the primary care office. The proposed algorithm consists of three main stages. First; denoising of input data (digital recordings of heart sounds), via Wavelet Packet Analysis. Second; input vector preparation through the use of Principal Component Analysis and block processing. Third; classification of the heart sound using an Artificial Neural Network. Initial testing revealed the intelligent diagnostic system can differentiate between normal healthy heart sounds and abnormal heart sounds (e.g., murmurs), with a specificity of 70.5% and a sensitivity of 64.7%.[18]

1.6 Thesis layout

This research consists of six chapters. Chapter one is an introduction. Artificial Neural Networks are presented in chapter two. Chapter three shows human heart system. The proposed model (methodology) is described in chapter four. Results and discussions are shown in chapter five. Finally chapter six is conclusions and recommendations.

Chapter Two

Introduction to neural networks

2.1 The Neural Network

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well [8].

2.2 Use neural networks

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections given new situations of interest and answer "what if" questions, other advantages include [10]:

1. Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.
2. Self-Organization: An ANN can create its own organization or representation of the information it receives during learning time.
3. Real Time Operation: ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
4. Fault Tolerance via Redundant Information Coding: Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

2.3 Human and Artificial Neurons - investigating the similarities

2.3.1 The Human Brain Learns

Much is still unknown about how the brain trains itself to process information, so theories abound. In the human brain, a typical neuron collects signals from others through a host of fine structures called *dendrites*. The neuron sends out spikes of electrical activity through a long, thin stand known as an *axon*, which splits into thousands of branches. At the end of each branch, a structure called a *synapse* converts the activity from the axon into electrical effects that inhibit or excite activity from the axon into electrical effects that inhibit or excite activity in the connected neurons. When a neuron receives excitatory input that is sufficiently large compared with its inhibitory input, it sends a spike of electrical activity down its axon.

Learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on another changes [13].

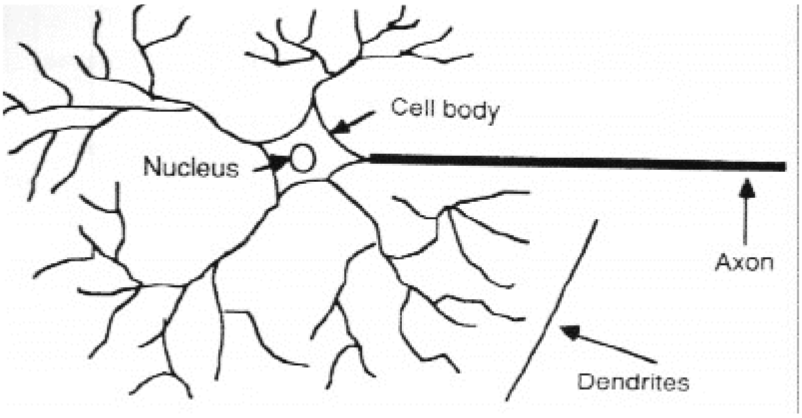

Figure 2.1: show component of neuron[7]

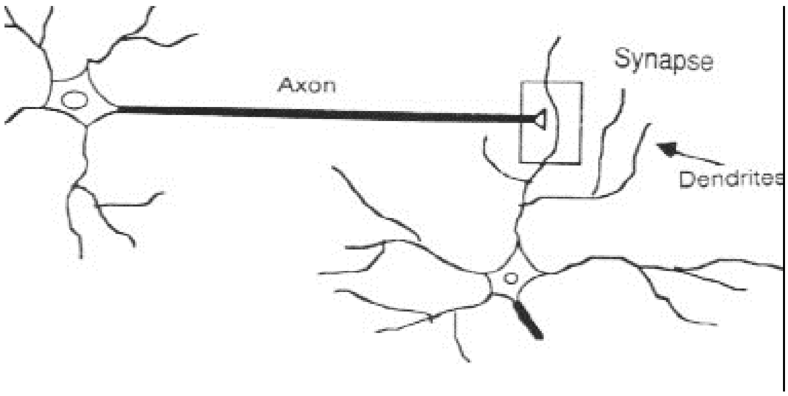

Figure 2.2: show cell body[7]

2.3.2 From Human Neurons to Artificial Neurons

We conduct these neural networks by first trying to deduce the essential features of neurons and their interconnections. We then typically program a computer to simulate these features. However because our knowledge of neurons is incomplete and our computing power is limited, our models are necessarily gross idealizations of real networks of neurons.

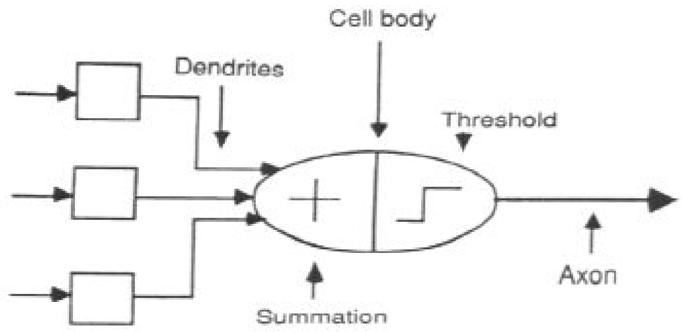

Figure 2.3: show the neuron model [7]

2.4 A simple neuron

An artificial neuron is a device with many inputs and one output. The neuron has two modes of operation; the training mode and the using mode. In the training mode, the neuron can be trained to fire (or not), for particular input patterns. In the using mode, when a taught input pattern is detected at the input, its associated output becomes the current output. If the input pattern does not belong in the taught list of input patterns, the firing rule is used to determine whether to fire or not.

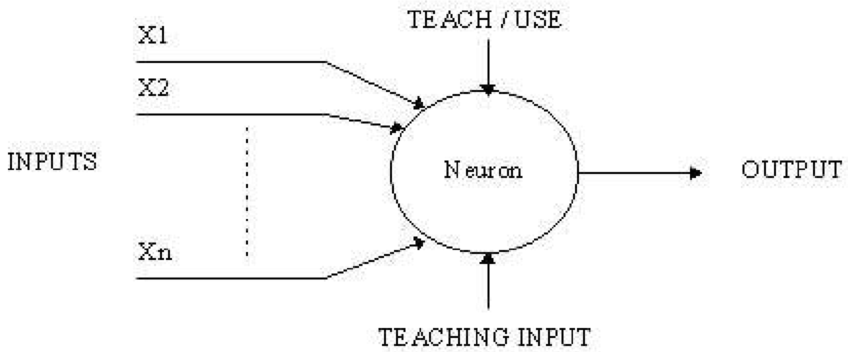

Figure 2.4 show a simple neuron[7]

2.5 The back-propagation Algorithm approach

Units are connected to one another. Connections correspond to the edges of the underlying directed graph. There is a real number associated with each connection, which is called the weight of the connection. We denote by w_{ij} the weight of the connection from unit ui to unit uj. It is then convenient to represent the pattern of connectivity in the network by a weight matrix W whose elements are the weights w_{ij}. Two types of connection are usually distinguished: excitatory and inhibitory. A positive weight represents an excitatory connection whereas a negative weight represents an inhibitory connection. The pattern of connectivity characterizes the architecture of the network.

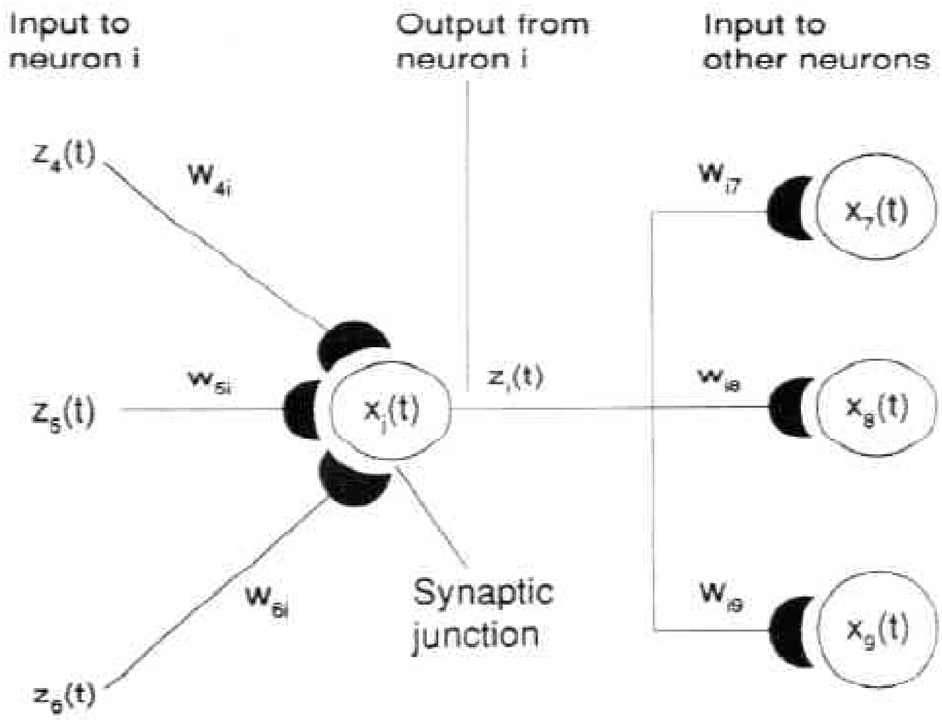

Figure 2.5: show the back-propagation Algorithm [10]

A unit in the output layer determines its activity by following a two steps procedure.

First, it computes the total weighted input xj, using the formula:

$$X_j = \sum_i y_i W_{ij} \qquad (1)$$

where yi is the activity level of the jth unit in the previous layer and Wij is the weight of the connection between the ith and the jth unit.

Next, the unit calculates the activity yj using some function of the total weighted input. Typically we use the sigmoid function:

$$y_j = \frac{1}{1+ e^{-x_j}} \qquad (2)$$

Once the activities of all output units have been determined, the network computes the error , which is defined by the expression:

$$E = \frac{1}{2} \sum_i (y_j - d_j)^2 \qquad (3)$$

where yj is the activity level of the jth unit in the top layer and dj is the desired output of the jth unit.

The back-propagation algorithm consists of four steps:

1. Compute how fast the error changes as the activity of an output unit is changed. This error derivative (EA) is the difference between the actual and the desired activity.

$$EA_j = \frac{\partial E}{\partial y_j} = y_j - d_j \qquad (1)$$

2. Compute how fast the error changes as the total input received by an output unit is changed. This quantity (EI) is the answer from step 1 multiplied by the rate at which the output of a unit changes as its total input is changed.

$$EI_j = \frac{\partial E}{\partial x_j} = \frac{\partial E}{\partial y_j} \times \frac{\partial y_j}{\partial x_j} = EA_j y_j (1 - y_j) \qquad (2)$$

3. Compute how fast the error changes as a weight on the connection into an output unit is changed. This quantity (EW) is the answer from step 2 multiplied by the activity level of the unit from which the connection emanates.

$$EW_{ij} = \frac{\partial E}{\partial W_{ij}} = \frac{\partial E}{\partial x_j} \times \frac{\partial x_j}{\partial W_{ij}} = EI_j y_i \qquad (3)$$

4. Compute how fast the error changes as the activity of a unit in the previous layer is changed. This crucial step allows back propagation to be applied to multilayer networks. When the activity of a unit in the previous layer changes, it affects the activites of all the output units to which it is connected. So to compute the overall effect on the error, we add together all these seperate effects on output units. But each effect is simple to calculate. It is the answer in step 2 multiplied by the weight on the connection to that output unit.

$$EA_i = \frac{\partial E}{\partial y_i} = \sum_i \frac{\partial E}{\partial x_j} \times \frac{\partial x_j}{\partial y_i} = \sum_i EI_j \, W_{ij} \qquad (4)$$

By using steps 2 and 4, can be convert the EAs of one layer of units into EAs for the previous layer. This procedure can be repeated to get the EAs for as many previous layers as desired. Once we know the EA of a unit, we can use steps 2 and 3 to compute the EWs on its incoming connections.

2.6 Architecture of neural networks

2.6.1 Feed-forward networks

Feed-forward ANNs allow signals to travel one way only; from input to output. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. Feed-forward ANNs tend to be straight forward networks that associate inputs with outputs. They are extensively used in pattern recognition. This type of organization is also referred to as bottom-up or top-down.

2.6.2 Feedback networks

Feedback networks can have signals travelling in both directions by introducing loops in the network. Feedback networks are very powerful and can get extremely complicated. Feedback networks are dynamic; their 'state' is changing continuously until they reach an equilibrium point. They remain at the equilibrium point until the input changes and a new equilibrium needs to be found. Feedback architectures are also referred to as interactive or recurrent, although the latter term is often used to denote feedback connections in single-layer organizations.

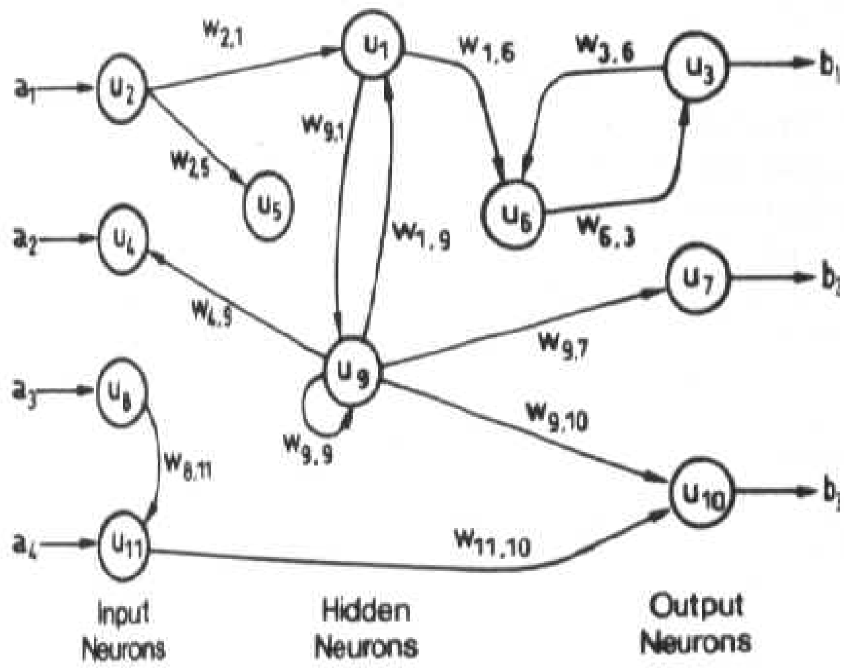

Figure 2.6: An example of a simple feed forward network[9]

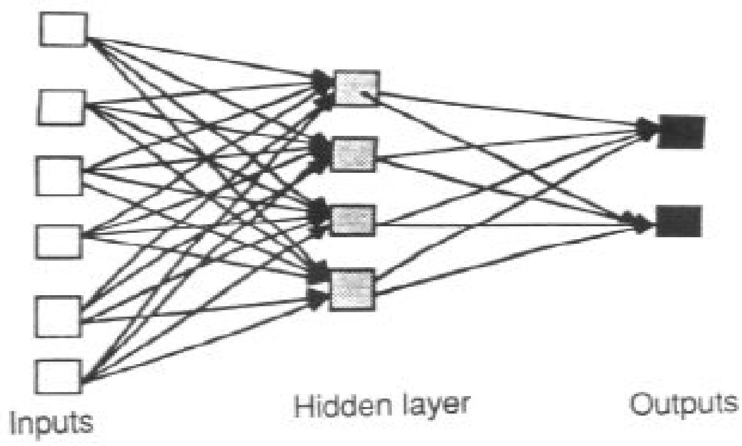

Figure 2.7 An example of a complicated network [9]

2.4.3 Network layers

The commonest type of artificial neural network consists of three groups, or layers, of units: a layer of "**input**" units is connected to a layer of "**hidden**" units, which is connected to a layer of **"output**" units.

The activity of the input units represents the raw information that is fed into the network.

The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units.

The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

This simple type of network is interesting because the hidden units are free to construct their own representations of the input. The weights between the input and hidden units determine when each hidden unit is active, and so by modifying these weights, a hidden unit can choose what it represents.

We also distinguish single-layer and multi-layer architectures. The single-layer organization, in which all units are connected to one another, constitutes the most general case and is of more potential computational power than hierarchically structured multi-layer organizations. In multi-layer networks, units are often numbered by layer, instead of following a global numbering.

2.8 Perceptron

The most influential work on neural nets in the 60's went under the heading of 'perceptrons' a term coined by Frank Rosenblatt. The perceptron (figure 2.8) turns out to be an MCP model (neuron with weighted inputs) with some additional, fixed, preprocessing. Units labeled A1, A2, Aj ,Ap are called association units and their task is to extract specific, localized featured from the input images. Perceptron mimic the basic idea behind the mammalian visual system. They were mainly used in pattern recognition even though their capabilities extended a lot more.

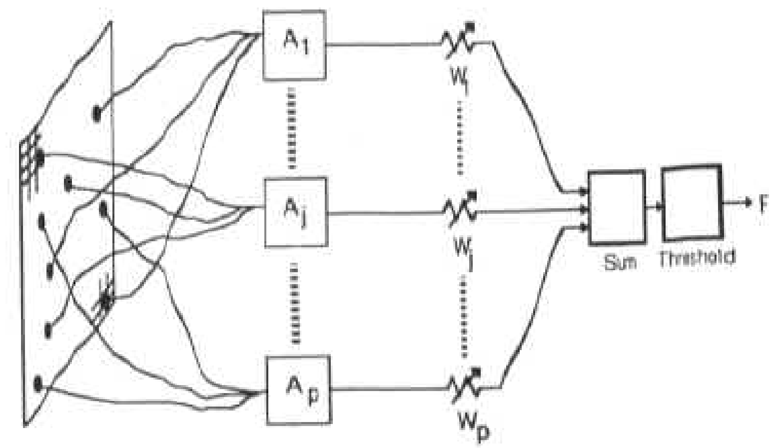

Figure 2.8 show the perceptron [8]

In 1969 Minsky and Papert wrote a book in which they described the limitations of single layer Perceptrons. The impact that the book had was tremendous and caused a lot of neural network researchers to lose their interest. The book was very well written and showed mathematically that *single layer* perceptrons could not do some basic pattern recognition operations like determining the parity of a shape or determining whether a shape is connected or not. What they did not realized, until the 80's, is that given the appropriate training, multilevel perceptrons can do these operations [13].

2.9 The Learning Process

The memorization of patterns and the subsequent response of the network can be categorized into two general paradigms:

- **Associative mapping** in which the network learns to produce a particular pattern on the set of input units whenever another particular pattern is applied on the set of input units. The associtive mapping can generally be broken down into two mechanisms:

1. Auto-association: an input pattern is associated with itself and the states of input and output units coincide. This is used to provide pattern completition, ie to produce a pattern whenever a portion of it or a distorted pattern is presented. In the second case, the network actually stores pairs of patterns building an association between two sets of patterns.
2. hetero-association: is related to two recall mechanisms:

- Nearest-neighbour recall, where the output pattern produced corresponds to the input pattern stored, which is closest to the pattern presented.
- Interpolative recall, where the output pattern is a similarity dependent interpolation of the patterns stored corresponding to the pattern presented. Yet another paradigm, which is a variant associative mapping, is classification, ie when there is a fixed set of categories into which the input patterns are to be classified.

- **Regularity detection** in which units learn to respond to particular properties of the input patterns. Whereas in associative mapping the network stores the relationships among patterns, in regularity detection the response of each unit has a particular 'meaning'. This type of learning mechanism is essential for feature discovery and knowledge representation.

Every neural network possesses knowledge which is contained in the values of the connections weights. Modifying the knowledge stored in the network as a function of experience implies a learning rule for changing the values of the weights.

Information is stored in the weight matrix W of a neural network. Learning is the determination of the weights. Following the way learning is performed, we can distinguish two major categories of neural networks:

- **fixed networks** in which the weights cannot be changed, iedW/dt=0. In such networks, the weights are fixed a priori according to the problem to solve.
- **Adaptive networks** which are able to change their weights, iedW/dt not= 0.

All learning methods used for adaptive neural networks can be classified into two major categories:

- **Supervised learning** which incorporates an external teacher, so that each output unit is told what its desired response to input signals ought to be. During the learning process global information may be required. Paradigms of supervised learning include error-correction learning, reinforcement learning and stochastic learning, an important issue concerning supervised learning is the problem of error convergence, ie the minimization of error between the desired and computed unit values. The aim is to determine a set of weights which minimizes the error.

One well-known method, which is common to many learning paradigms is the least mean square (LMS) convergence.

- **Unsupervised learning** uses no external teacher and is based upon only local information. It is also referred to as self-organization, in the sense that it self-organizes data presented to the network and detects their emergent collective properties. Paradigms of unsupervised learning are Hebbianlerning and competitive learning, Ano2.2 from Human Neurons to Artificial Neurons there aspect of learning concerns the distinction or not of a separate phase, during which the network is trained, and a subsequent operation phase. We say that a neural network learns off-line if the learning phase and the operation phase are distinct. A neural network learns on-line if it learns and operates at the same time. Usually, supervised learning is performed off-line, whereas usupervised learning is performed on-line[9].

2. 10 Transfer Function

The behavior of an ANN (Artificial Neural Network) depends on both the weights and the input-output function (transfer function) that is specified for the units. This function typically falls into one of three categories:

1. linear (or ramp)

2. threshold
3. sigmoid

For **linear units**, the output activity is proportional to the total weighted output.

For **threshold units**, the output are set at one of two levels, depending on whether the total input is greater than or less than some threshold value.

For **sigmoid units**, the output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neurons than do linear or threshold units, but all three must be considered rough approximations.

To make a neural network that performs some specific task, we must choose how the units are connected to one another, and we must set the weights on the connections appropriately. The connections determine whether it is possible for one unit to influence another. The weights specify the strength of the influence.

2.11 Multilayer perceptron:-

A **multilayer perceptron** (MLP) is a feedforward artificial neural network model that maps sets of input data onto a set of appropriate outputs. A MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training the network. MLP is a modification of the standard linear perceptron and can distinguish data that are not linearly separable.

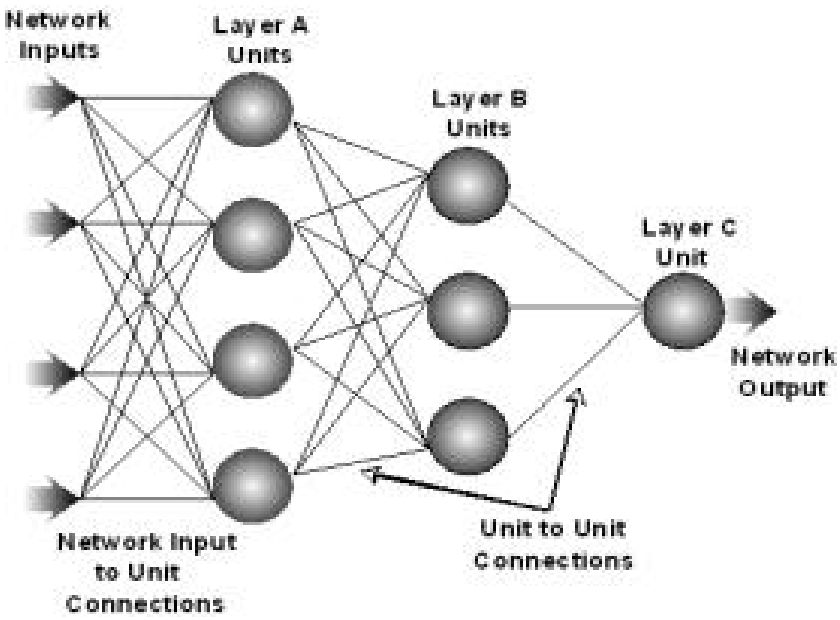

Figure 2.9 show the Multilayer perceptron [10]

2.11.1 Activation function

If a multilayer perceptron has a linear activation function in all neurons, that is, a linear function that maps the weighted inputs to the output of each neuron, then it is easily proved with linear algebra that any number of layers can be reduced to the standard two-layer input-output model . What makes a multilayer perceptron different is that each neuron uses a *nonlinear* activation function which was developed to model the frequency of action potentials, or firing, of biological neurons in the brain.[10]

2.11.2 Layers

The multilayer perceptron consists of three or more layers (an input and an output layer with one or more *hidden layers*) of nonlinearly-activating nodes and is thus considered a deep neural network. Each node in one layer connects with a certain weight to every node in the following layer. Some people do not include the input layer when counting the number of layers and there is disagreement about whether should be interpreted as the weight.

2.11.3 Learning through backpropagation

Learning occurs in the perceptron by changing connection weights after each piece of data is processed, based on the amount of error in the output compared to the expected result.

2.11.4 Applications

Multilayer perceptrons using a backpropagation algorithm are the standard algorithm for any supervised learning pattern recognition process and the subject of ongoing research in computational neuroscience and parallel distributed processing. They are useful in research in terms of their ability to solve problems stochastically, which often allows one to get approximate solutions for extremely complex problems like fitness approximation.

MLPs were a popular machine learning solution in the 1980s, finding applications in diverse fields such as speech recognition, image recognition, and machine translation software,[5] but have since the 2000s faced strong competition from the much simpler (and related[6]) support vector machines. More recently, there has been some renewed interest in backpropagation networks due to the successes of deep learning.

Chapter three

Heart Murmurs

Before proceeding to the system design, an overview of the heart is presented including physiology of heart, the pumping cycle of heart and heart murmur types. Exiting methods for heart murmur detection/ classification are also discussed.

3.1 Physiology of Heart :

Human heart plays a fundamental role in the pumping of blood circulation throughout the body. Figure (3.1) show a human heart and to provide a brief introduction to the reader about the working of heart, a short tour of heart physiology is provided. Heart consists of four chambers namely left ventricle, right ventricle, left atrium and right atrium

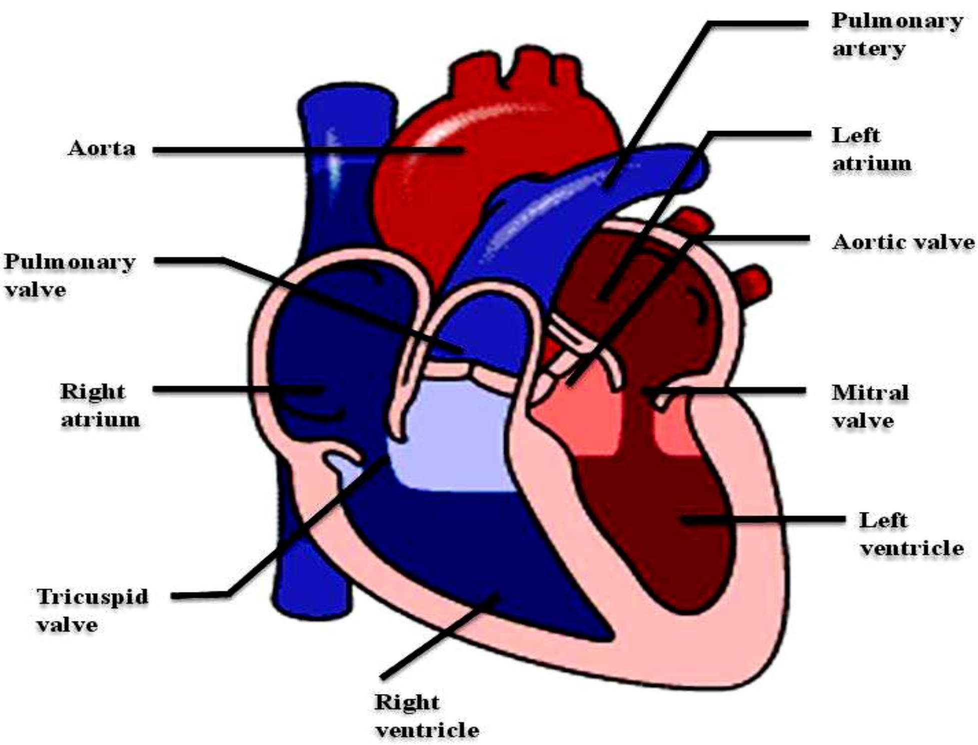

Figure 3.1:Human heart [1]

Deoxygenated blood coming from the body first arrives in the right atrium, after the right ventricle is filled, the blood is pushed towards the lungs where it is oxygenated and sent back to left atrium. From left atrium blood flows towards left ventricle and as soon as left ventricle is filled, heart contracts and blood is sent to whole body.

A block diagram would be better helpful in understanding the whole process, blood flows from the body and the lungs at the same time. De-oxygenated blood first arrives to the right atrium and then flows towards right ventricle through tricuspid valve. After the blood is filled right ventricle, it is pushed towards the lungs through the pulmonary valve. The same procedure is repeated with the oxygenated blood coming from the lungs and pushed towards the body through left atrium and then left ventricle using mitral valve and aortic valves, as shown in the figure (3.2).

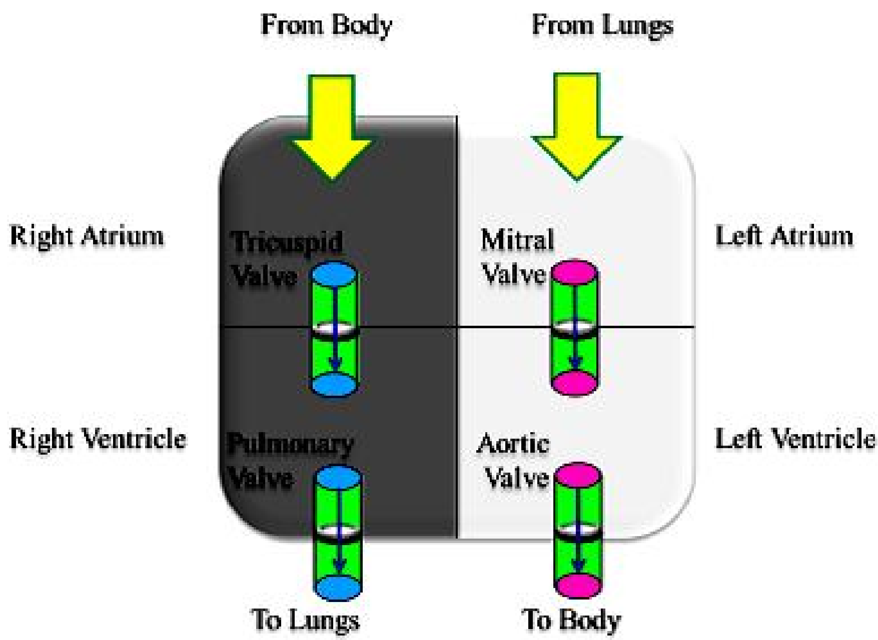

Figure 3.2: Block diagram of pumping cycle of heart[5]

3.2 **Pumping Cycle of the Heart:**

The pumping cycle of the heart is divided into two parts – the systole and diastole. The period of contraction is called systole and the period of relaxation, diastole. The heart sounds ‗lub – dub' occur at the time of the closure and opening of the major heart valves, respectively. The first heart sound or S1 (‗lub') occurs at the start of systole, and the second heart sound or S2 (‗dub') occurs during diastole [5]. Figure (3.3) shows a single cycle of heart sound with S1 and S2 labeled.

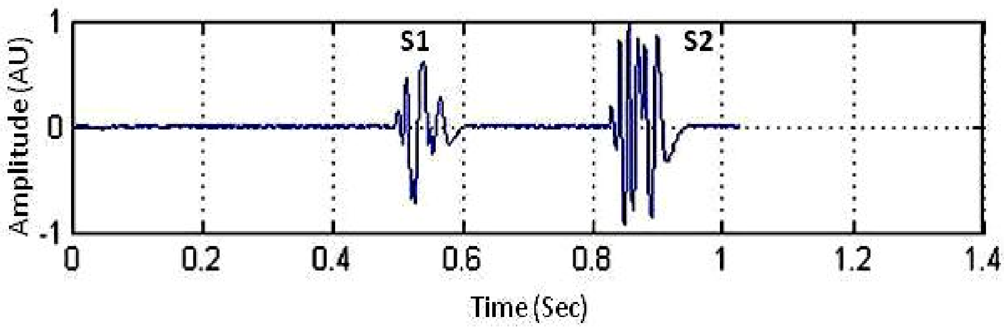

Figure 3.3 Typical heart sound single cycle[15]

3.3 Normal Heart Sound and Murmur Types:

If the heart is working normally, the heart sounds consist of cycles of S1 and S2 only. However, if there is a heart malfunction (e.g., a major valve not closing or fully opening properly), heart murmurs can be heard in the heart pumping cycle during auscultation [6]. Usually, extraneous heart murmur sounds are quieter than the S1 and S2 sounds, especially if the malfunctioning of the heart is at an early stage [7].

Extraneous heart sounds can occur during either the systolic or diastolic periods of the heart cycle. An extraneous heart sound occurring during the systolic period (i.e., between S1 and S2) is called a systolic murmur. Similarly, an extraneous heart sound occurring during the diastolic period (i.e., between S2 and S1), is called a diastolic heart murmur. The two most common types of systolic and diastolic murmurs are aortic stenosis (AS) and aortic regurgitation (AR) respectively, as shown in figure (3.4) along with a normal heart sound.

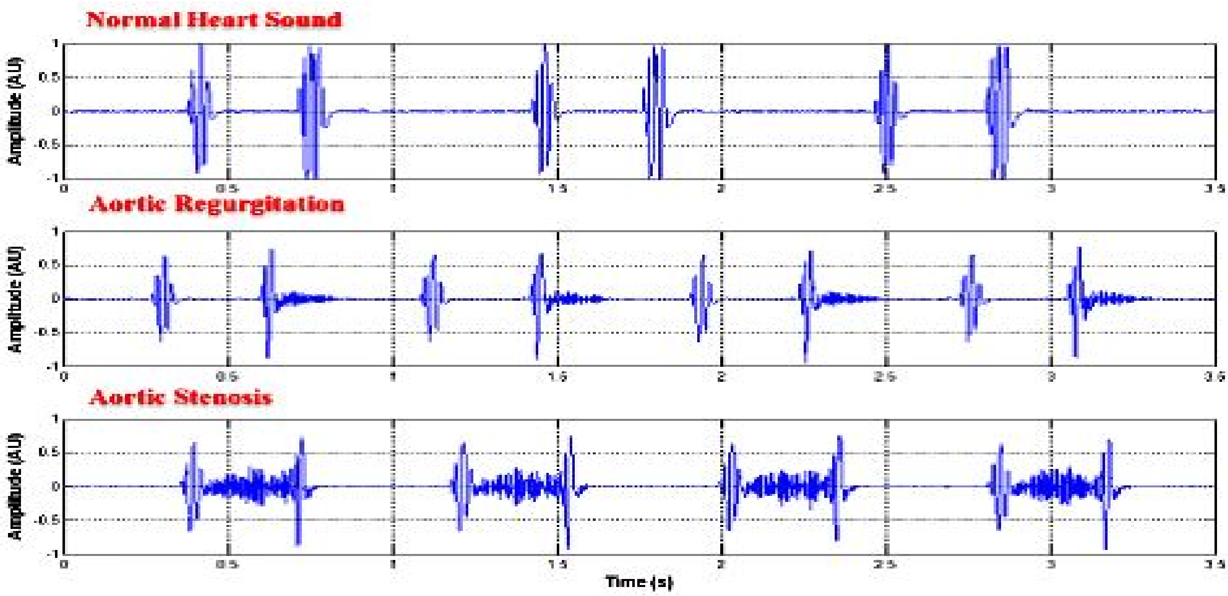

Figure 3.4 :(a) normal heart sound , (b)AS and (c)AR[15]

3.4 causes a heart murmur :

3.4.1 Functional heart murmur

Many heart murmurs are harmless and referred to as innocent or functional. They are caused when blood rushes through the heart quickly during normal function while no heart disease may exist. There may be an underlying medical condition that can lead to an innocent murmur. These may include situations where the heart beats more quickly such as fever, anemia, hyperthyroidism, and pregnancy.

3.4.2 Congenital heart murmurs

Congenital heart murmurs are heard in the newborn. They may be due to abnormalities in the valves, septae or arteries, and veins that carry blood to and from the heart. In some complicated heart disease conditions there may be a combination of all three. Many congenital heart murmurs resolve spontaneously without medical intervention while others require surgical operations for repair.

Patent ductusarteriosus (PDA) may cause a heart murmur in a newborn. Prior to birth birth, the aorta and pulmonary artery are connected by a small artery, the ductusarteriosus, to complete fetal blood circulation. Shortly after birth, this artery is supposed to close. If other congenital heart abnormalities exist, the ductus may remain open to help maintain some blood circulation. Sometimes, when no congenital abnormalities exist, the ductus doesn't completely close and a murmur may exist. Many times the patent ductusarteriosus closes by itself over time. Occasionally, medications or surgery may be required to close off the patent ductusarteriosus.

3.4.3 Valve abnormalities

Abnormalities of the valves of the heart may cause a heart murmur. Any of the heart valves may be affected and clinical symptoms depend upon the severity of the valve damage and whether the blood flow pattern within the heart is maintained. Each valve problem often leads to a specific character and timing of heart murmur.

3.5 The risk factors for heart murmur:

A heart murmur is a physical finding of an underlying heart condition and in many instances may be of no consequence. The risk factor for developing a particular murmur is the risk factor for underlying condition.

Congenital heart disease tends to have a familial basis, meaning that there may be a genetic predisposition for a baby to develop a structurally abnormal heart.

Some valvular diseases are present at birth, but take a lifetime to develop symptoms. For example, the aortic valve is supposed to have three leaflets that come together; some people are born with a valve that has only two leaflets (bicuspid). Over time, a two-leafed valve may be more prone to calcification and narrowing. Symptoms may only be seen later in life.

Some valve diseases are due to infection and past rheumatic fever with heart valve inflammation due to a bacterial streptococcus infection. With present day screening for strep infections and the appropriate use of antibiotics, this risk factor has decreased significantly.

Other risk factors for heart valve abnormalities include atherosclerotic heart disease, heart attack, aortic aneurysm, and connective tissue disorders such as systemic lupus erythematosus and Marfan syndrome. Each condition affects the valves in a different way causing them to malfunction and develop the physical finding of a heart murmur.

Chapter Four

The proposed system

4.1 System Overview

In this work, a diagnostic system is implemented that can help to reduce the number of echocardiograms that are ordered for healthy patients. The diagnostic system is based on an easy-to-use graphical user interface that has been designed using MATLAB software and the ANN Toolbox. The system allows the user to interactively design and create a heart sound classification system .the proposed system model show in figure (4.1) below:

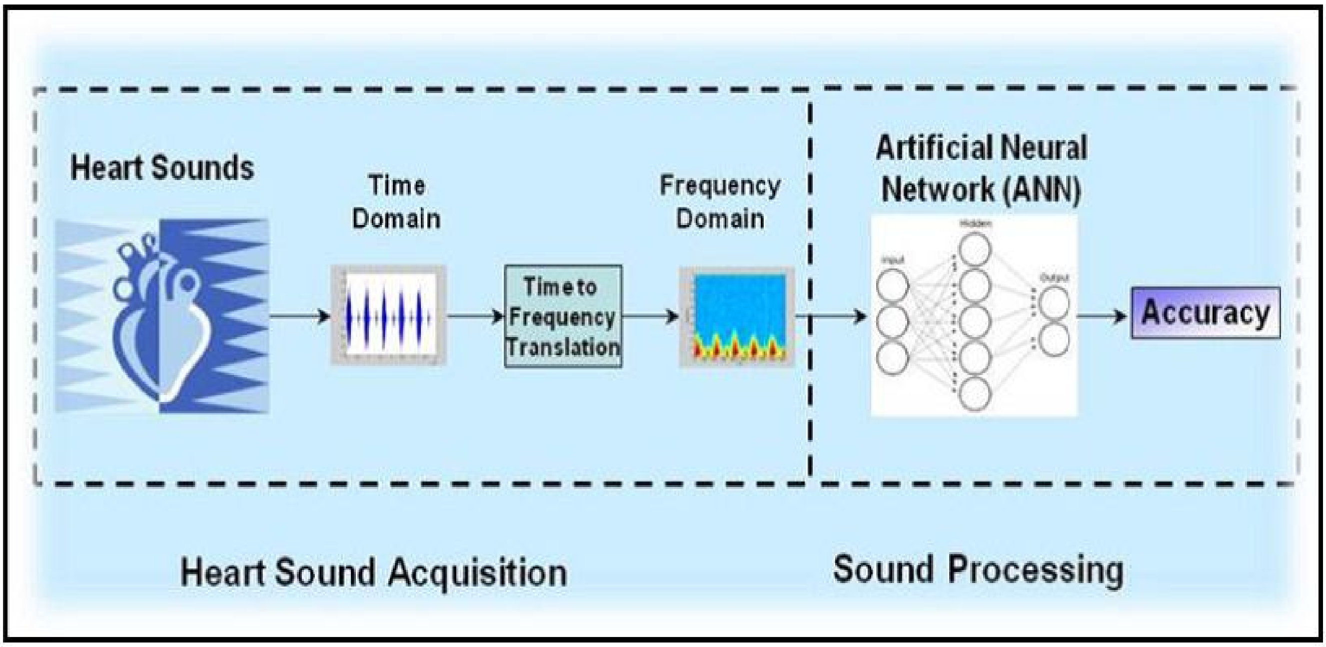

Figure 4.1: shown System diagram

After a classifier has been designed and created, the user is able to select any audio files on his or her computer to use as input to the ANN system. In the event that a patient has a heart sound that is difficult for physicians to diagnose, the classifier could reduce the tendency of the physician to refer the patient to echocardiogram when the procedure is not necessary. The signals are processed through embedded sophisticated signal processing algorithms before a final diagnosis can be made. The block diagram of the processed is depicted in figure (4.2).

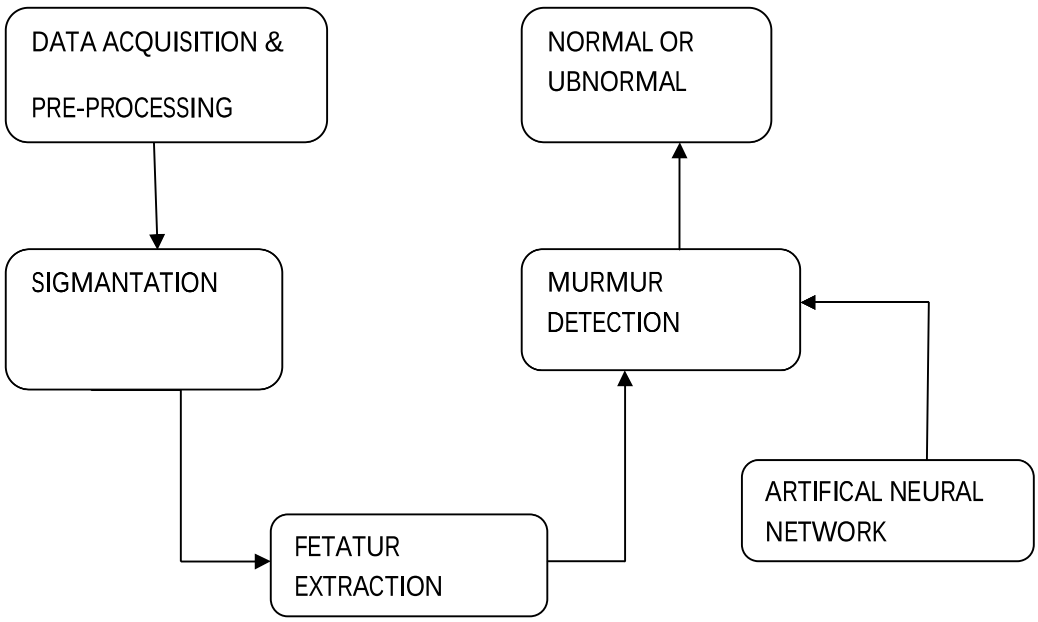

Figure 4.2 : block digram of signal processing

To show the system's ability to classify heart sounds, testing has been performed using the ANN classifier to distinguish between normal heart sound and, murmurs.

4.2 Data Acquisition and pre-processing

To design and test the ANN system, a heart sound data base consisting of 35 simulated heart sounds is used. The simulated heart sounds were obtained from internet(Classifying Heart Sounds Challenge .htm # dates) . The patient sounds used for testing in this research include 10 examples of normal, 25 examples of murmurs. The heart sound data that is provided to the complete system must be in .wav audio format. These sounds transferring to a computer. Heart sounds of virtually any heart rate or duration can be inputted to the system. The sounds were then digitized with a sampling rate of 8 KHz, 16 bits/sample. The digitized signal was then used as input to the segmentation algorithm.

4.3 Heart sound segmentation

A segmentation algorithm is applied to compute the representative single heart cycle for that sound. The segmentation algorithm is used to identify the heart sound components S1 and S2. Once the positions of these components are located, individual heart cycles can be identified and the average of all the cycles within the sound is computed. The heart cycle obtained from the averaging process will be the one that represents the particular sound under study. Next, the alignment algorithm inputted into the ANN system for the design (or test) phase. The first pre-processing step uses a segmentation algorithm to identify the heart sound components S1 and S2 within the original heart sound show in (Fig4.2).

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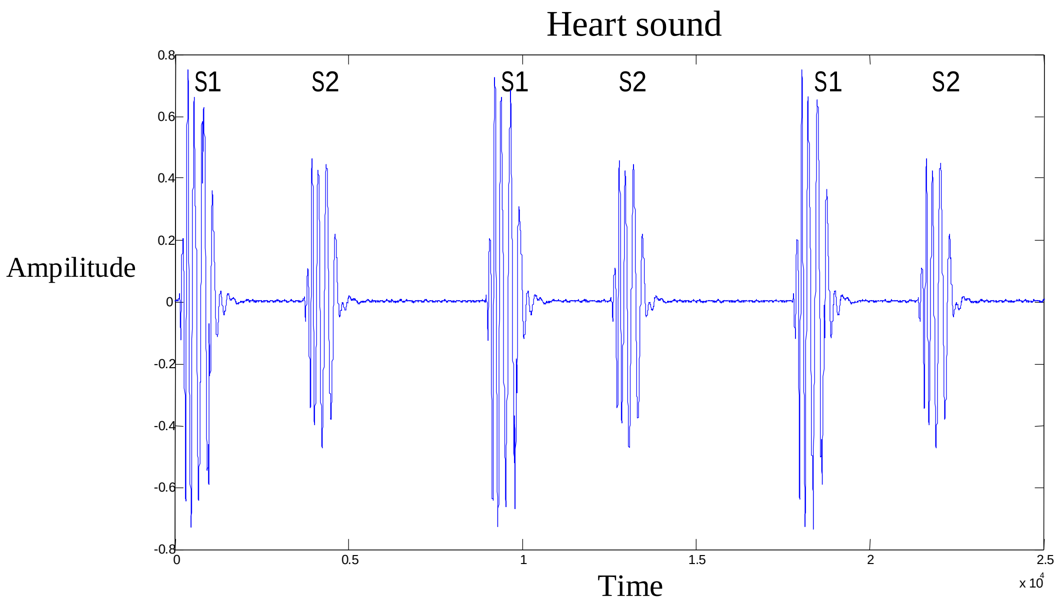


Fig 4.3. The time vs. amplitude plot of a heart sound .

The segmentation method uses the components of S1 and S2 that occur at low frequency levels relative to murmurs.

S1 and S2 are identified based on the timing between those high amplitude components. The fact that the time from S1 to S2 (systole) is always less than the time from S2 to S1 (diastole) is the basis for this algorithm.

Once the S1s and S2s are located, the individual heart cycles within the heart sound can be identified and resample to normalize their lengths. Only a single heart cycle is used for the analysis and classification of the sound. Instead of taking any of the individual cycles from a heart sound for the analysis, the average of the single cycles is computed and the resulting averaged heart cycle for that heart sound will be the one that is processed and inputted into the ANN for design (or testing) show in (Fig.4.4). The whole algorithm was implemented in Matlab.

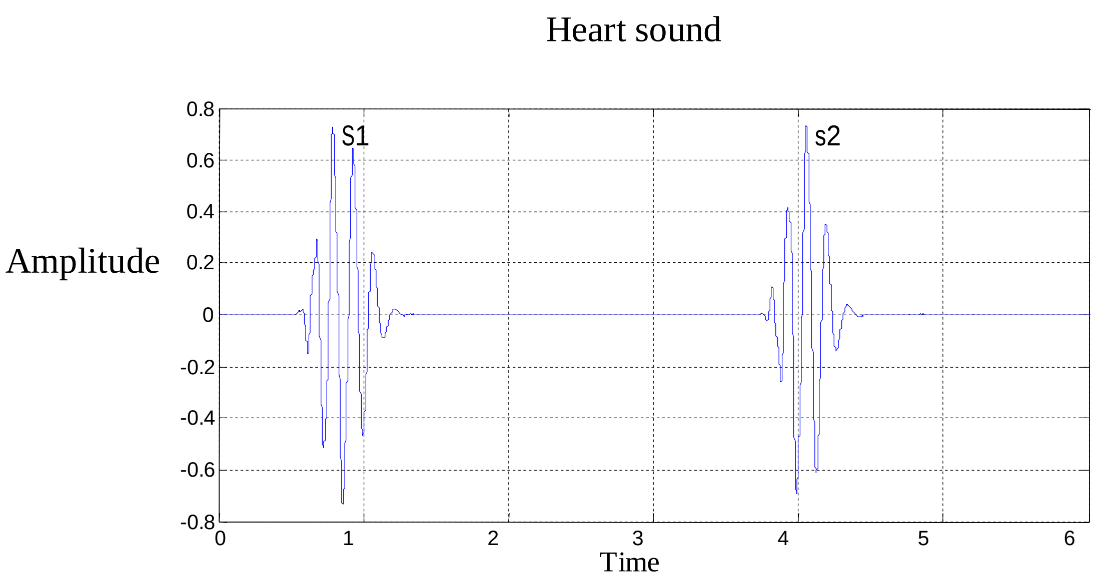


Fig 4.4. The average heart cycle—the result of averaging together the single cycles found by applying the segmentation algorithm to the heart sound in Fig. 1.

4.4. Feature Extraction using Spectrogram

The features are extracted from individual systolic and diastolic periods using Spectrogram which is a window based Fast Fourier Transform (FFT). Matlab command to calculate the windowed discrete time Fourier transform using a sliding window called specgram. Next the spectrogram was divided into 10 segments of equal length and the maximum amplitude in each segment was taken as a feature as shown in figure (4.5).

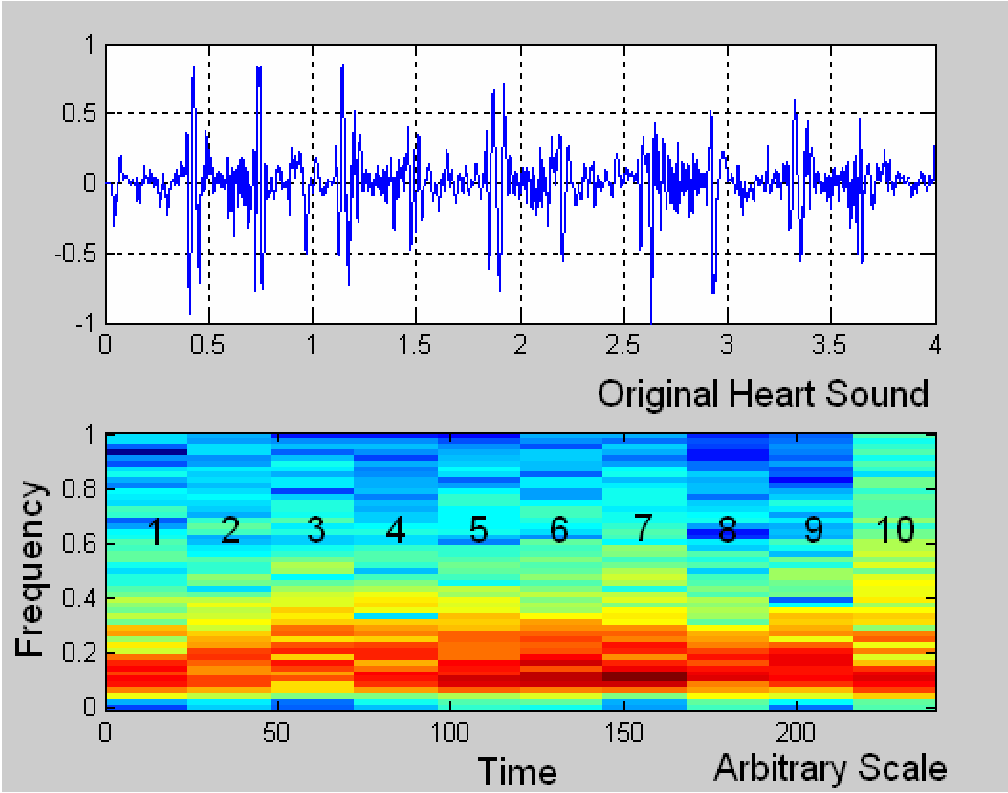


Figure 4.5: Feature extraction using spectrogram

In order to automate the whole feature extraction step, Matlab was linked with Microsoft Access. The features were then exported to the database directly.

4.5 ANN Architecture Used to Create the Classifier

Back-propagation was used as the traini algorithm for the feed-forward ANN classifier since it is recognized as a good algorithm for the purpose of pattern recognition. The results shown in this research are from an ANN system using 3 hidden layers with 25 neurons each, 25 input neurons, one output neuron, training mean squared error goal of 0.0005. These parameters were optimized by repetition and comparison, with consideration from previous work.

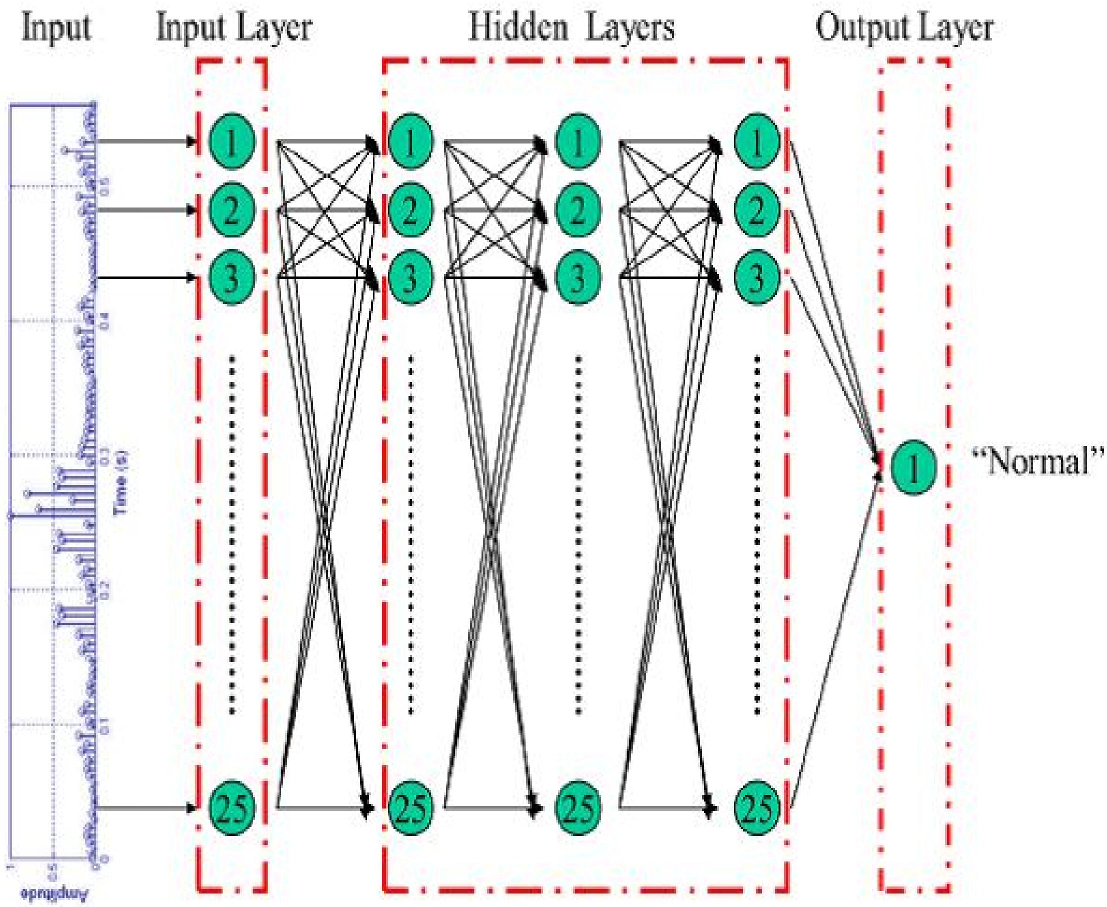


Figure 4.6: Artificial neural network (ANN)

4.6 Procedure Used to Test the ANN System

Once the ANN classifier has been designed and created, the user can observe output results using either the test set(s) or any other heart sounds on their computer. An output is then provided which indicates which training target is most similar to the current test input.

A comparison of the simulated heart sounds used in this research to heart sounds data shows that the sounds compare closely after some filtering. Thus, designing the system with simulated sounds is expected to yield useful results for testing both simulated and patient-recorded heart sounds.

Chapter five

Results and Discussion

The patient sounds used for testing in this research obtained from internet (Classifying Heart Sounds Challenge.htm#dates) include 10 examples of normal, 25 examples of murmurs. The simulated heart sounds were used to test our ANN 35 sounds (10 normal) for training and 25 for testing as presented in the table (5.1) below

Table (5.1) : Heart sounds data used

Heart sound category	Training samples	Testing samples
Normal	5	5
Murmurs	-	25
Total	5	30
	35	

5.1 Normal heart sound training:-

From the result in table (5.2) training regression value and mean square for normal heart sound show below

Table (5.2): Normal heart sound training (regression and MSE)

Normal heart sound	Regression value FFB	Mean Square Error (MSE)
N1	.99999	1.58909*10-10
N2	.97998	1.59939*10-10
N3	.99998	6.37247*10-8

After training, ANNs able to detect the normal and murmrs sounds. there are many different between normal heart sound and mururs sound by the value and figure of regression ,the figure(5.1) below show the plot of normal heart sound training :

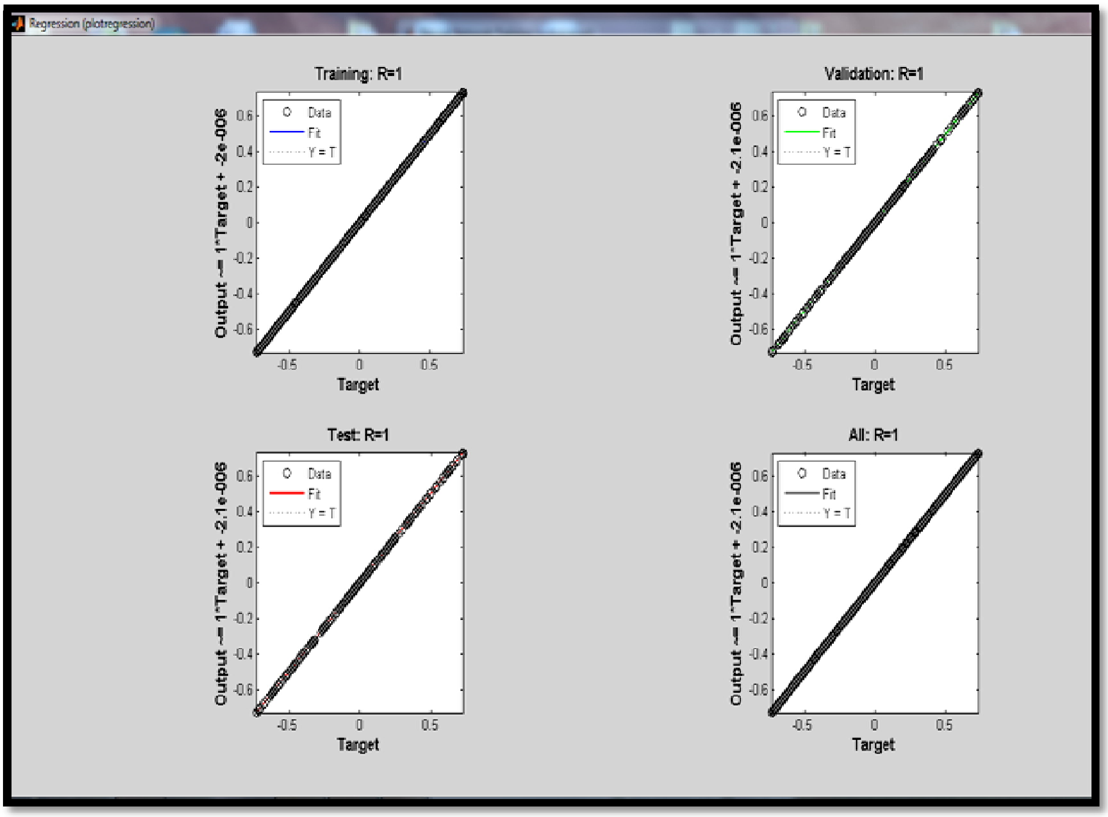


Figure (5.1) : plot regression after training

Two ANNs structures are used in the classification process to obtain the best classification accuracy.

The study for detection has been carried out using Back propagation- feed forward (BPFF) and multi-layer Perceptron (MLP).

5.2 The samples used for testing the (BPFF) network is show in table (5.3):-

Table (5.3): regression and classification using (BPFF)

Number sound	Regression value (BPFF)	Classification
s1	0.0051	Murmur
s2	0.0056	Murmur
s3	0.0347	Murmur
s4	0.0456	Murmur
s5	0.0130	Murmur
s6	0.0074	Murmur
s7	0.7176	Normal
s8	0.0088	Murmur
s9	0.0127	Murmur
s10	0.0073	Murmur
s11	0.0657	Murmur
s12	00128	Murmur
s13	0.9999	Normal
s14	0.0408	Murmur
s15	0.0131	Murmur
s16	0.0095	Murmur
s17	0.8340	Normal
s18	0.0218	Murmur
s19	0.0073	Murmur
s20	0.0074	Murmur

s21	0.9989	Normal
s22	0.8995	Normal
s23	0.0008	Murmur
s24	0.0111	Murmur
s25	0.0064	Murmur
s26	0.9953	Normal
s27	0.0352	Murmur
s28	0.0387	Murmur
s29	0.0075	Murmur
s30	0.0030	Murmur
s31	0.0237	Murmur
s32	0.0133	Murmur
s33	0.0219	Murmur
s34	0.6641	Normal
s35	0.0345	Murmur

5.3 The samples used for testing the (MLP) network is show in table (5.4) :-

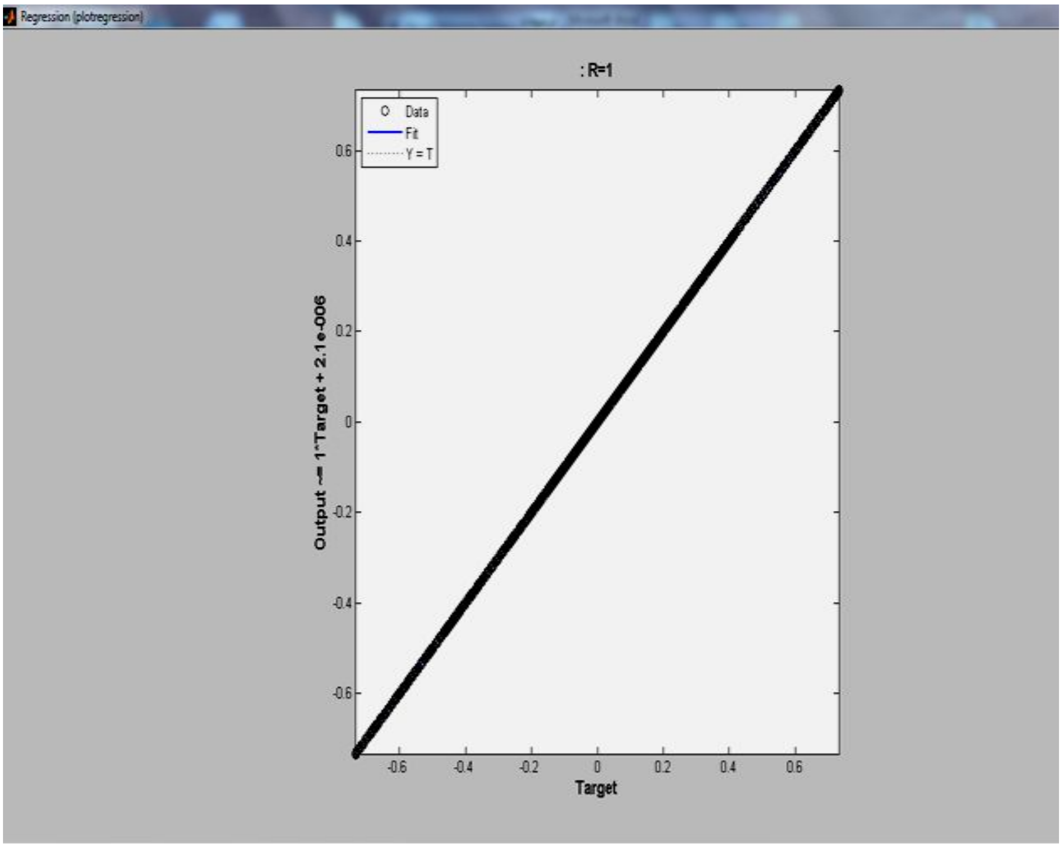
Table (5.4): regression and classification using (MLP)

Number sound	Regression value (MLP)	Classification
S1	0.0510	Murmur
S2	0.543	Normal
S3	0.304	Murmur
S4	0.0455	Murmur

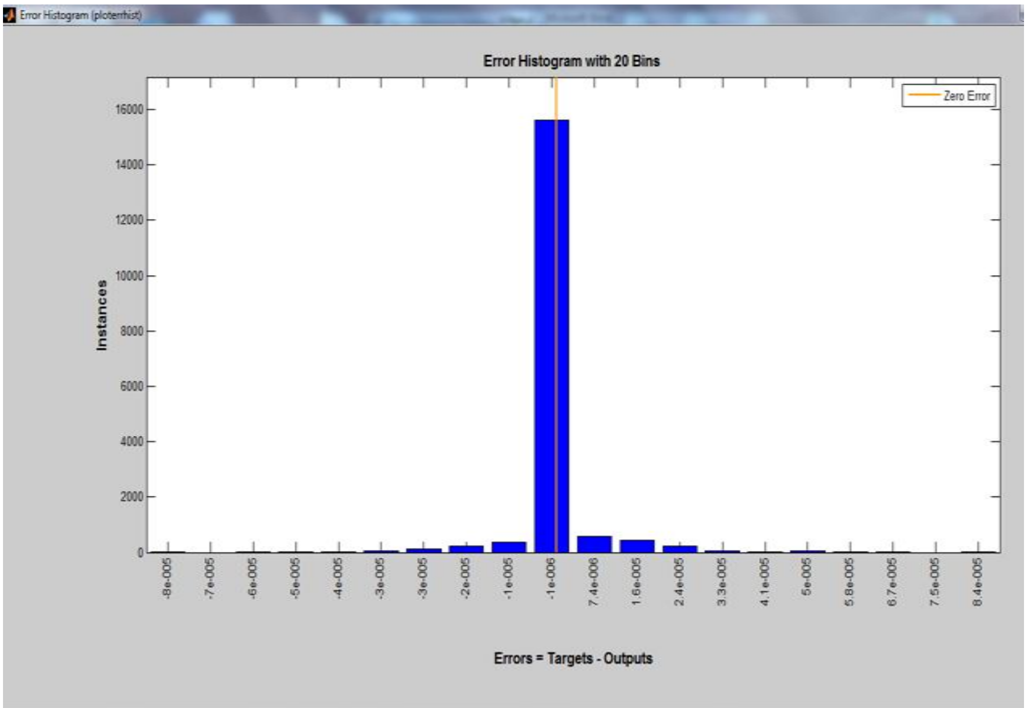
S5	0.6539	Normal
S6	0. 8550	Normal
S7	0.0531	Murmur
S8	0.0872	Murmur
S9	0.135	Murmur
S10	0.0742	Normal
S11	0.065	Murmur
S12	0.128	Murmur
S13	0.845	Normal
S14	0.330	Murmur
S15	0.094	Murmur
S16	0.756	Normal
S17	0.253	Murmur
S18	0.0743	Murmur
S19	0.7661	Normal
S20	0.0784	Murmur
S21	0.799	Normal
S22	0.667	Normal
S23	0.0553	Murmur
S24	0.0179	Murmur
S25	0.0111	Murmur
S26	0.00639	Murmur
S27	0.5963	Normal
S28	0.00756	Murmur
S29	0.00307	Murmur
S30	0.0732	Murmur

S31	0.0443	Murmur
S32	0.0361	Murmur
S33	0.0123	Murmur
S34	0.999	Normal
S35	0.0659	Murmur

After testing the neural network the plot of regression for the normal heart sound illustration in figure (5.2) and mean square error in figure (5.3):

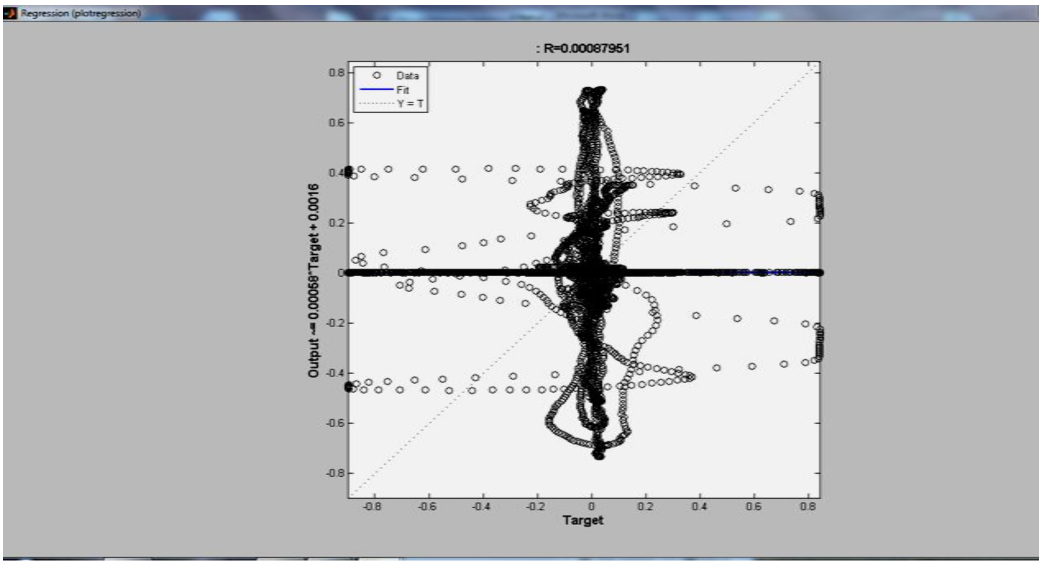


Figure(5.2): plot regression for normal

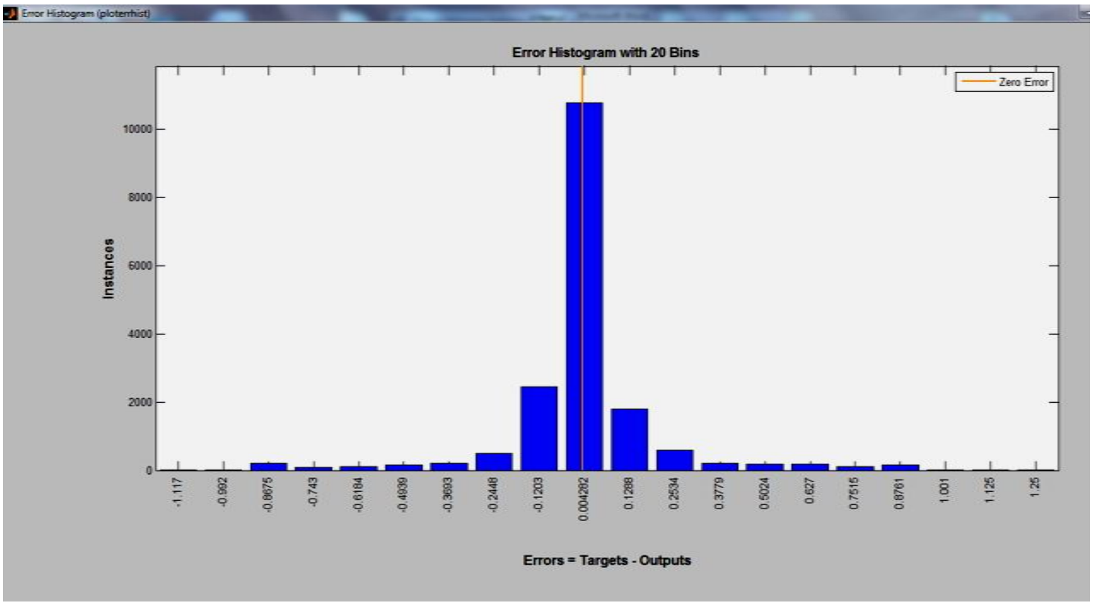


Figure(5.3): plot mean square error normal

After testing the neural network the plot of regression for the murmur heart sound illustration in figure (5.4) mean square error in figure (5.5) :



Figure(5.4): plot regression murmur



Figure(5.5): plot mean square error murmur

Results of comparative studies:-

5.4 Performance evaluation of ANNs :-

Sensitivity is a very important measure for this particular research since it is a measure of the percentage of patients with unhealthy hearts that are recognized as such. Specificity is the percentage of healthy cases that are classified as healthy.

The accuracy of the ANN system is compared by antier ANN system accuracy. However, the general trend were calculated and tabulated in table (5.5):

Table (5.5): ANNs performance

Performance Measure	BPFF	MLP
sensitivity	94%	96%
specificity	60%	95%
accuracy	90%	97%

Chapter six

Conclusion and Recommendation

6.1 Conclusion

The auscultative accuracy rate of the average physician is clearly low, and this fact leads to the referral of healthy patients for echocardiogram. Unnecessary referral to this costly procedure could be reduced if an inexpensive yet reliable diagnostic tool were available as an aide for physicians. The software system proposed in this work attempts to provide such a tool.

The software system provides the user with an output classification for an unknown heart sound , and this information could prove useful for a physician to consider when deciding whether or not to refer a patient for echocardiogram. It is expected that future research in noise reduction methods will lead to even better rates of classification.

6.2 Recommendation

1. Better noise reduction/ removal technique can also be used to clean the signals before processing the heart sounds.
2. Advance this research by incorporating more murmur types and testing heart sounds from real patients.
3. Suggested to use of other types of neural network and comparative results to reach to the best usages.

References

[1] Garson A, Bricker J, McNamara D. *“The Science and Practice of Pediatric Cardiology”.* Philadelphia, Pa: Lea & Febiger; 1990.

[2] Pelech A. The cardiac murmur. *Pediatr Clin North Am..* 1998.

[3] Rangaraj M, Murthy I, “Quantitative analysis of the phonocardiogram for detection of murmurs”. *J Biomed Eng.* 1979.

[4] Lok C, Morgan C, Ranganathan N. The accuracy and intraobserver agreement in detecting the ‘gallop sounds’ by cardiac auscultation. *Chest.* 1998.

[5] VanOort A, Le Blanc-Botden M, De-Boo T, et al. The vibratory innocent heart murmur in school children: difference in auscultatory findings between school medical officers and a pediatric cardiologist. *Pediatr Cardiol*. 1994.

[6] Pelech A. Evaluation of the pediatric patient with a cardiac murmur. *Pediatr Clin North Am..* 1999.

[7] Cathers I. Neural network assisted cardiac auscultation. *Artif Intell Med.* 1995.

[8] Crick F. The recent excitement about neural networks. *Nature.* 1989.

[9] Hinton G. How neural networks learn from experience. *Sci Am.* 1992.

[10] Tu J. Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes. *J Clin Epidemiol.* 1996.

[11] Guo Z, Durand L, Lee H, et al. Artificial neural networks in computer assisted classification of heart sounds in patients with porcine bioprosthetic valves. *Med Biol Eng Comp*. 1994.

[12] Coehn M, Hudson D. *Comparative Approaches to Medical Reasoning*. River Edge, NJ: World Scientific; 1995.

[13] Binder T, Sussner M, Moertl D, et al. Artificial neural networks: theoretical considerations and clinical applicability. *Comput Biol Med.* 1999.

[14] Itchhaporia D, Snow P, Almassy R, et al. Artificial neural networks: current status in cardiovascular medicine. *J Am Coll Cardiol.* 1996.

[15] Waqas Ahmad ,Heart Murmur Detection/ Classification using Cochlea-like Pre-processing, January 2010

[16] Andrisevic N, Ejaz K, Rios-Gutierrez F, Alba-Flores R, Nordehn G, Burns S, Detection of heart murmurs using wavelet analysis and artificial neural networks, 2005 Nov

[17] Strunic, S.L.; Rios-Gutierrez, F. ; Alba-Flores, R. ; Nordehn, G., Detection and Classification of Cardiac Murmurs using Segmentation Techniques and Artificial Neural Networks, March 1 2007-April .

[18] Nicholas Andrisevic, Glenn Nordehn, Stanley Burns, Khaled Ejaz, Fernando Rios-Gutierrez and Rocio Alba-Flores , Detection of Heart Murmurs Using Wavelet Analysis and Artificial Neural Networks, July 08, 2005

[19] Bates, B., *A Guide to Physical Examination and History Taking*. 9th Ed 2005.

[20] Von Békésy, G. Experiments in Hearing . New York: McGraw-Hill (1960).

[21] R. F. Lyon and C. Mead, ―An analog electronic cochlea‖ , IEEE Trans. Acoustics, Speech, and Signal Processing,1989.

[22] C. N. Gupta, et al., ―Segmentation and classification of heart sounds‖ , CCECE/ CCCGEI, Saskatoon, IEEE, 1996.

[23] F. Baumgarte, ―A computationally efficient cochlear filter bank for perceptual audio coding, proceedings of Acoustics, Speech, and Signal Processing, 2001.Proceedings. 2001 IEEE International Conference on, 2001.

[24] Malcolm Slaney, ―Lyon‘s Cochlear Model,‖ Apple Technical Report #13 (available from the Apple Corporate Library, Cupertino, CA 95014), 1988.

[25] Zaiton Sharif, Shaparas Daliman, A. Z. Zuri, Sha´ameri, and S. H. S. Salleh, ―An Expert System Approach for Classification of Heart Sounds and Murmurs ‖ Sixth International Symposium on Signal Processing and its Applications (ISSPA), 2001.

[26] S. L. Strunic, F. Rios-Gutierrez, R. Alba-Flores, G. Nordehn, S. Burns, ―Detection and classification of cardiac murmurs using segmentation techniques and artificial neural networks ‖, Proceedings of the 2007 IEEE symposium on computational intelligence and data mining (CIDM 2007).

[27] K. Ejaz, G. Nordehn, R. Alba-Flores, F. Rios-Gutierrez, S. Burns, and N. Andrisevic, ―Heart murmur detection system using spectrograms artificial neural networks ‖, IASTED Conference: Circuits, Signals and Systems (CSS 2004), 2004 .

[28] Toshiyuki Nakamitsu, Hideaki Shino, Tomoya Kotani, Kazuo Yana, Kensuke Harada, Jiro Sudoh, Eishi Harasawa, and Hideki Itoh ―Detection and Classification of Systolic Murmur Using a Neural Network ‖ Proceedings of the 1996 Fifteenth Southern Biomedical Engineering Conference, 1996 .

[29] T.R. Reed, N.E. Reed and P. Fritzson , The Analysis of Heart Sounds for Symptom Detection and Machine-added Diagnosis Proceedings of the 4th International EUROSIM Congress, Delft, The Netherlands, June 26-29,.

[30] H. Shino, H. Yoshida, K. Yana, K. Harada, J. Sudoh, and E. Harasewa, ―Detection and Classification of Systolic Murmur using a Neural Network□ Proc. 18th Ann. Int. Conf. of the IEEE, EMBS, 1996, 2001

[31] Faizan javed, P A Venkatachalam, Ahmad Fadzil M H , ―A Signal Processing Module for the Analysis of Heart Sounds and Heart Murmurs□, J. Phys.: Conf. Ser, 2006 .

[32] S. A. Pavlopoulos, A. C. Stasis, and E. N. Loukis, ―A Decision Tree-Based Method, Using Auscultation Findings for the Differential Diagnosis of Aortic Stenos is from Mitral Regurgitation□, Biomed. Eng. Online, 2004.

[33] Z. Sharif, M. S. Zainal, A. Z. Sha'ameri, and S. H. S. Salleh, ―Analysis and Classification of Heart Sounds and Murmurs Based on the Instantaneous Energy and Frequency Estimates□ , Proc. of TENCON, Kuala Lumpur, 2000.

[34] Turkoglu, A. Arslan, and E. Ilkay, ―An Intelligent System for Diagnosis of the Heart Valve Diseases with Wavelet Packet Neural Networks□, Comput. Biol. Med, 2003.

[35] C. G. DeGroff, S. Bhatikar, J. Hertzberg, R. Shandas, L. Valdes-Cruz, and R. L. Mahajan, , 2001 ―Artificial Neural Network-Based Method of screening Heart Murmurs in Children□, Circulation, 2001 .

[36] R. Collobert and S. Bengio ,Links between Perceptrons, MLPs and SVMs. Proc. Int'l Conf. on Machine Learning (ICML), (2004).

Appendix A

MATLAB code to get the regression

```
 net=setx(net,w);
y=sim(net,s1);
r=corrcoef(y,l);
R=r(1,2)
```

MATLAB code for data detection

```
fprintf('enter the data\n');
X=input('enter ur data as matrix');
X(s1)=sigm((s1));
X=abs(X(s1));
net=setx(net,w);
y=sim(net,s1);
r=corrcoef(x,y);
z=r(1,2)
R=abs(z)
If 1> R> 0.5
      disp('The patient is normal')
Else
      Disp('The patient is murmur)
end
```

Appendix B

A comparison of results for heart murmur detection and classification systems from literature is shown in table 6 below.

Table 6: Comparison of results from theoretical foundation

Ref	Kind of sound used	Type of heart sound	AI techniques used	Accuracy and sensitivity
Waqas Ahmad January 2010	simulated	Normal,AR,AS	Cochlea like preprocessing artificial neueal network	Accuracy 100%
S.L.Strunic,F.Rios,S.Burns Nov 2005	Simulated and recorded patients	Normal,aortic stenosis, aortic regurgitation	Artificial neural network	Accuracy 85 % Sensitivity 95 %
Computational Intelligence and Data Mining March 2007	Simulated and recorded patients	Normal , type of murmur	Artificial neural network	Accuracy 85plusmn7.4% Sensitivity 95plusmn6.8%
Nicholas,Glenn,Stanley,Khaled Fernando and rocio July 2005	Digital record of heart sound	Normal, murmurs	Artificial neural network	Specificity 70.5% Sensitivity 64.7%
Wahiba Hamdan Ali May 2014	Simulated data from Internet	Normal, murmurs	Artificial neural network	Accuracy90%,97% Sensitivity 94%,96%

Appendix C

Statistics - definitions

True positive: Sick people correctly diagnosed as sick

False positive: Healthy people incorrectly identified as sick

True negative: Healthy people correctly identified as healthy

False negative: Sick people incorrectly identified as healthy

true positive (TP)

true negative (TN)

false positive (FP)

false negative (FN)

sensitivity or true positive rate (TPR):

$$TPR = TP/P = TP / (TP + FN) \qquad (1)$$

specificity (SPC) or True Negative Rate:

$$SPC = TN/N = TN/ (FP + TN) \qquad (2)$$

accuracy (ACC):

$$ACC = (TP + TN)/(P + N) \qquad (3)$$