DETERMINING BRAIN ILLNESS IMAGES BY USING ARTIFICIAL NEURAL NETWORK

by

Elif ERDOĞAN

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APPROVAL PAGE

I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science.

Assist. Prof. Dr. Tuğrul Yanık
Deputy Head of Department

This is to certify that I have read this thesis and that in my opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

Prof. Dr. Bekir KARLIK
Supervisor

Examining Committee Members

Prof. Dr. Bekir KARLIK :

Prof. Dr. Sadık KARA :

Assist. Prof. Dr. İhsan Ömür BUCAK :

It is approved that this thesis has been written in compliance with the formatting rules laid down by the Graduate Institute of Sciences and Engineering.

Assist. Prof. Nurullah Arslan
Deputy Director

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M. S. Thesis - Computer Engineering
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Supervisor: Prof. Dr. Bekir KARLIK

ABSTRACT

The aim of this study is to develop a method to learn brain diseases by using Magnetic Resonance (MR) images. Artificial Neural Network (ANN) approach is used to diagnose and classify brain diseases including tumor, meningitis and seizure. ANN is used in this application because of its learning ability. Backpropagation is used as learning algorithm. MR images are used to diagnose brain diseases. Sample MR images were collected from Radiology department of Fatih University Hospital.

In the first part of the study, preprocessing methods are applied to the MR images to obtain same size features. To reduce large and redundant data, feature extraction method is used. Firstly, images are divided into small pieces having size of 30x30 pixels. For each subdivision, arithmetic mean is calculated to obtain feature vector which will be used as system input.

In the second part, ANN is designed and generated. Feature vector is fed to the network (ANN) in the training phase. Then application is tested with inputs which are not used in the training phase and the results are observed.

Consequently, this application is developed to help physicians in diagnosis of various brain diseases using an intelligent model. It aims to show benefits of ANN model to reduce diagnosis complexity and faults arising from subjective evaluations of physicians or unclear data.

Keywords: Artificial Neural Network (ANN), Image Processing, Backpropagation Algorithm, Brain Diseases, Tumor, Meningitis, Seizure.

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ÖZ

Bu çalışmanın amacı, Manyetik Rezonans (MR) görüntülerini kullanarak beyin hastalıklarını öğrenebilen bir metot geliştirmektir. Hastalıkların tümör, menenjit ve inme olarak teşhis edilmesinde ve sınıflandırılmasında Yapay Sinir Ağları (YSA) yaklaşımı kullanılmıştır. YSA, öğrenme yeteneğinden dolayı tercih edilnmiştir. Öğrenme algoritması olarak geri yayılım algoritması kullanılmıştır. MR görüntüleri. Beyin hastalıklarını teşhisinde kullanılan örnek MR görüntüleri Fatih Üniversitesi Hastanesi Radyoloji bölümünden alınmıştır.

Çalışmanın birinci bölümünde, aynı özellikte görüntüler elde edebilmek için MR görüntülerine önişlem uygulanmaktadır. Gereksiz ve fazla olan data miktarının azaltılması için öznitelik çıkarım metotları kullanılmıştır. Öncelikle resim 30x30 pixelden oluşan küçük karelere ayrılmıştır. Her karenin aritmetik ortalaması hesaplanarak, sistem girişi olarak kullanılacak olan öznitelik vektörü elde edilmiştir.

İkinci kısımda ise, YSA tasarımı yapılmıştır. Eğitim safhasında, öznitelik vektörü sisteme giriş olarak verilmiş, daha sonra eğitim safhasında kullanılmayan veriler ile sistem test edilmiş ve sonuç izlenmiştir.

Sonuç olarak geliştirilen uygulama ile çeşitli beyin hastalıklarını teşhisinde doktorlara yardımcı olabilecek akıllı bir sistem tasarlanmıştır. YSA kullanılarak teşhiste olabilecek hatalar en aza indirgenmeye çalışılmıştır.

Keywords: Yapay Sinir Ağları, Resim İşleme, Geri Yayılım Algoritması, Beyin Hastalıkları, Tümör, Menenjit, İnme.

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LIST OF SYSMBOLS AND ABBREVIATIONS

2DFT	Two-Dimensional Fourier Transform
3DFT	Tree-Dimensional Fourier Transform
ANN	Artificial Neural Network
CBF	Cerebral Blood Flow
CBV	Cerebral Blood Volume
CT	Computed Tomography
CSF	Cerebrospinal Fluid
DRA	Deficit Reduction Act
DWT	Discrete Wavelet Transform
EPI	Echo-Planar Imaging
FFT	The Fast Fourier Transform
GNRR	General Regression Neural Network
LBBB	Left and Right Bundle Branch Block
LVQ	Learning Vector Quantization
MR	Magnetic Resonance
MRI	Magnetic Resonance Imaging
MSE	Mean Square Error
NMRI	Nuclear Magnetic Resonance Imaging
NN	Neural Network
RBFN	Radial Basis Function
RNN	Recurrent Neural Networks
RBBB	Right Bundle Branch Block
SOM	Self-Organizing Map

CHAPTER 1

INTRODUCTION

Neural Network (NN) or Artificial Neural Network (ANN) is introduced to solve the complex nonlinear problems which the conventional analytical methods cannot easily solve. By resembling the human brain, the neural network works as a parallel distributed processor made up of simple processing units (neurons), which have a natural capability for storing experiential knowledge and making it available for generalization (Haykin, 1999) .

NNs are used in pattern recognition because of their ability to learn and to store knowledge. Because of their 'parallel' nature can achieve, Neural network can achieve very high computation rates which is vital in application like telemedicine (Siganos, 1995).

ANN which is a system based on the human brain, is a powerful technique to solve many real world complex problems. ANNs have the ability to learn from experience. They can adapt themselves to changes in the environment so they can keep and improve their performance. When the rules or formulas for the problem are not well defined ANN can be used effectively and also ANNs can be used with noisy data.

ANNs are adaptive models for the analysis of data which are inspired by the functioning processes of the human brain. ANNS are able to modify their internal structure in relation to a function objective. They are particularly suited for solving problems of the non linear type (Lisboa, 2002).

ANNs are being used widely in the field of medicine. They are suited to problems with a high degree of complexity for which there is no algorithmic solution or the solution is too complex for traditional techniques to determine. Medical areas have successful ANN implementations such as drug development, patient diagnosis, and image analysis.

ANNs have been applied to an increasing number of real-world problems of considerable complexity. Considered as good pattern recognition engines and robust classifiers, with the ability to generalize in making decisions about imprecise input data, they offer ideal solutions to a variety of problems such as, prediction and modeling where the physical processes are not understood or are highly complex. The analysis of cancer survival is used to determine the efficiency of treatment programs and protocols; it is also used to determine the type of treatment. At the individual level a prediction of cancer survival can help patients make informed decisions with regards to the quality of life and finance. Currently available prediction methods apply to groups of people and may not be adequate to predict treatment outcome of individual patients (Sameen, 2001)

NNs are ideal in recognizing diseases using scans since there is no need to provide a specific algorithm on how to identify the disease. NNs learn by example so the details of how to recognize the disease are not needed. What is needed is a set of examples that are representative of all the variations of the disease. The quantity of examples is not as important as the 'quantity'. The examples need to be selected very carefully if the system is to perform reliably and efficiently (Stergiou and Siganos, 1996).

Medicine has always benefited from the forefront of technology. Technology advances like computers, lasers, ultrasonic imaging, etc. have boosted medicine to extraordinary levels of achievement. ANN is currently the next promising area of interest. It is believed that neural networks will have extensive application to biomedical problems in the next few years. Already, it has been successfully applied to various areas of medicine, such as diagnostic systems, biochemical analysis, image analysis, and drug development. ANNs are extensively used in diagnostic systems like detecting cancer and heart problems. ANNs are a used in chemistry applications like analyzing blood and urine samples, tracking glucose levels in diabetics, determining ion levels in body fluids and

pathological conditions such as tuberculosis. ANNs are used in the analysis of medical images as tumor detection in ultra-sonograms, classification of chest x-rays, tissue and vessel classification in magnetic resonance images (MRI), determination of skeletal age from x-ray images, and determination of brain maturation. ANNs are used in the development of drugs for treating cancer and AIDS (Siganos, 1996).

In this study, a system which can recognize and classify the brain diseases from MR images, is designed and presented. ANN model is used because of its learning ability. ANN has the ability of learning from samples and producing an output for the inputs which are not used at the learning phase.

This study consists of four steps:

The first step is data collection. MR images related with the brain diseases are collected from Radiology department of Hospital of Fatih University. Sample images are collected from 120 different patients and 30 samples for each disease. 20 of 30 samples are used for learning phase and 10 of them are used for testing phase.

The second step is the preprocessing of data. Varying dimensions of the sample images are a problem. To solve this problem, resizing method is performed on MR images and new sizes of all samples are fixed as 240 x 240 pixels. Some images have unnecessary data like patient names or times etc. These parts are removed from the images to keep the accuracy of application.

The third step is feature extraction. The input data is transformed into a reduced representation which means a small subset of features. To obtain feature vector which has smaller dimension, images are divided into 8 equal smaller parts vertically and horizontally. Thus, 64 subdivisions are obtained (8x8=64) and arithmetic mean is calculated for each subdivision. Feature vector has 64 elements which represent arithmetic mean of each subdivision and it means that input vector has 64 nodes in the system. The last step is implementation. Backpropagation and supervised learning algorithm are used for the ANN model. Inputs are given to designed ANN system and then results are observed.

1.1 LITERATURE SURVEY

Medicine has always benefited from the forefront of technology. Technology advances like computers, lasers, ultrasonic imaging, etc. have boosted medicine to extraordinary levels of achievement. Artificial Neural Networks (ANN) is currently the next promising area of interest. It is believed that neural networks will have extensive application to biomedical problems in the next few years. Already, it has been successfully applied to various areas of medicine, such as diagnostic systems, biochemical analysis, image analysis, and drug development. Recently, many ANN and the other soft computing applications in Medicine have been proposed.

Karlık, Şahin, Ercan, Tavlı (2006) has presented a paper to detect Left and Right Bundle Branch Block (LBBB and RBBB) by using ANNs and to transmit classification results of ECG signals from the patient's home to the research hospital via internet for diagnosis, because LBBB and RBBB represents an independent predictor of poor outcome in myocardial infarction.

ANNs are used experimentally to implement electronic noses. Electronic noses have several potential applications in telemedicine. Telemedicine is the practice of medicine over long distances via a communication link. The electronic nose would identify odors in the remote surgical environment. These identified odors would then be electronically transmitted to another site where a door generation system would recreate them. Because the sense of smell can be an important sense to the surgeon, telesmell would enhance telepresent surgery (Stergiou and Siganos, 1996).

Breast cancer is the second largest cause of cancer deaths among women. The automatic diagnosis of breast cancer is an important, real-world medical problem. A major class of problems in medical science involves the diagnosis of disease, based upon various tests performed upon the patient. When several tests are involved, the ultimate diagnosis may be difficult to obtain, even for a medical expert. This has given rise, over the past few decades, to computerized diagnostic tools, intended to aid the physician in making sense out of the confusion of data. Neural network have been applied to breast cancer diagnosis (Kıyan and Yıldırım, 2004).

Kıyan and Yıldırım (2003) employed Radial Basis Function, General Regression Neural Network and Probabilistic Neural Network in order to get the suitable result. Diagnostic performance of GRNN and RBFN are compared.

Di Luca et al. (2005) aimed with their study to assess the efficacy of neural network in correctly classifying control subjects and mild Alzheimer Disease (AD) patients only on the basis of peripheral betaamyloid cascade biomarkers.

Gorban et al. (1995) described a neural software which is applied in medicine and physiology to: - investigate and diagnose immune deficiencies; diagnose and study allergic and pseudo allergic reactions; forecast emergence or aggravation of stagnant cardiac insufficiency in patients with cardiac rhythm disorders; forecast development of cardiac arrhythmia after myocardial infarction; reveal relationships between the accumulated radiation dose and a set of immunological, hormonal, and bio-chemical parameters of human blood and find a method to be able to judge by these parameters the dose value; propose a technique for early diagnosis of choroid melanomas; Neural networks help also to predict human relations within a group.

Temurtas et al.(2008) studied on diabetes disease diagnosis using neural networks. Their study presents a comparative study on Pima Indian diabetes disease diagnostic by using multilayer neural network which was trained by LM algorithm and probabilistic neural network. The results were also compared with the results of the previous studies. The results were also quite good. They presented that neural network structures could be successfully used to help diagnosis of pima-diabetes disease.

Ari and Saha (2008) have proposed an optimized ANN structure for automatic classification of heart sound signal by their study. Their ANN model gives 99.279% accuracy for 12 pathological cases and normal heart sound.

Das et al. (2008) was used to construct a neural networks ensemble-based methodology for diagnosing of the valvular heart disease.

Güven et al. (2005) used seven different ANN models were realized to determine the eye diseases such as optic nerve diseases from pattern electroretinography (PERG) and visual evoked potential (VEP), macular disease from PERG, subnormal eye from electrooculography (EOG) and diseases on the photoreceptor cells from electroretinography (ERG).

Çavdaroğlu (2006) studied on a brain model which was constructed by using brain MR images. The advantages of information technology combined with expertise, information and experiments.

Koca (2007) aimed to develop a method to learn the benign and malign tumors which were shown in the breast MR by giving contrast enhanced. Neural network was used for the learning ability of the application and backprogation was used for the learning algorithm.

In the study of Kul (2008), diagnosis of lumbar disc hernia from MR images was presented. Diagnosis was implemented by classification of MR images into predefined classes or categories. The ANN model learned from the samples of MR in training phase and it was tested with different data in testing phase.

CHAPTER 2

BIOLOGICAL NERVOUS SYSTEM

Biological nervous system is explained as a triple layer system which has a brain in its center and gets the information permanently, interprets this information and produces suitable results.

The input to the network of neurons is provided by receptors, which continually monitor changes in the external and internal environment. Cells called motor neurons (or motoneurons), governed by the activity of the neural network, control the movement of muscles and the secretions of glands. In between, an intricate network of neurons (a few hundred neurons in some simple creatures, hundreds of billions in a human brain) continually combines the signals from the receptors with signals encoding past experience to barrage the motor neurons with signals that will yield adaptive interactions with the environment. In animals with backbones (vertebrates, including mammals in general and humans particular), this network is called central nervous system (CNS), and the brain constitutes the most headword part of this system, linked the receptors and effectors of the body via the spinal cord (Arbib, 2002). Receptors convert internal and external signals into electrical signals which transfer data to the brain. Effectors convert electrical strokes, produced by brain, into suitable responses as organism output. A block model or nervous system is showed in Figure 2.1.

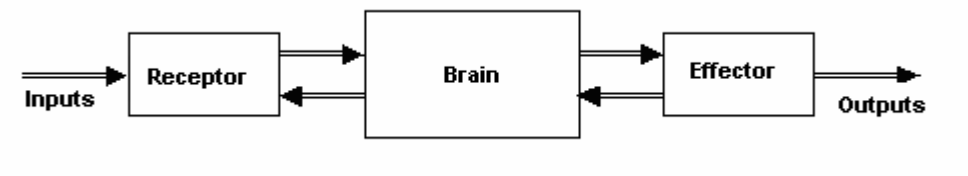

Figure 2.1 biological nervous systems as a block diagram

In the central nervous system the information is evaluated between receptors and effectors and in the direction of feedback and feedforward.

2.1 BASIC PROPERTIES OF NEURONS

To understand the processes that intervene between receptors and effectors, we must have a closer look at the neuron There is no such a thing a typical neuron. However we will summarize properties shared by neuron. From the soma (cell body) protrudes a number of ramifyinbranches called *dentrides*; the soma and dentrides constitute the input surface of the neuron. There also extrudes from the cell body, along fiber called *axon*. The tips of the branches of axon, called nerve terminals or buttons, impinge on other neurons or on effectors. The locus of interaction between a bouton and the cell on which it impinges is called a *synapse*, and we say that the cell with the bouton synapses upon the cell with which the connection is made. I fact, axonal branches of some neurons can have many varicosities, corresponding to synapses, along their length, not just at the end of branches. (Arbib, 2003) The basic neuron is shown in Figure 2.2.

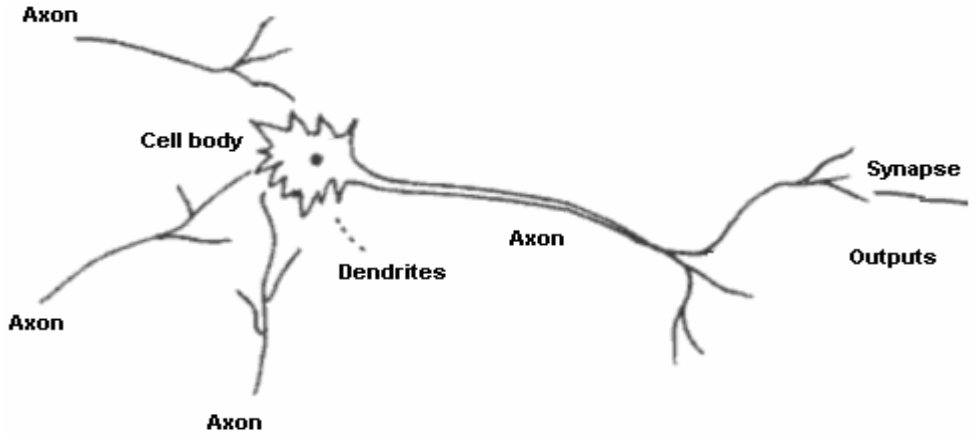

Figure 2.2 A basic neuron(Arbib, 2003)

To reach information which connections and relations are followed, which cell is weighted on the response, is decided. The connections of cells which reach desired information's weights are more than the others (Yurtoğlu, 2005).

Information arriving to synapse and taken by dendrites are generally electrical signals but affected by chemical transmitters in synapse. When the value of input arrives a cell in a certain time provides a threshold value, the cell produces a response. The inputs increasing cell responses are called as stimulative and decreasing cell responses are called as preventive. These responses are determined by synapse. The synapses provide connections between neurons. Hereby, it is determined that which neurons will be used to get information and which cells have bigger effect on final decision. The weight of the connection between neurons which conveys to the result is bigger than the other connections. Thus, nervous system can be able to provide data transmission between suitable neurons. Also that communicated structure adds the property of plasticity to the nervous system (Yurtoğlu, 2005).

Human brain consists of 10 billion neurons and 60 trillion synapses. So, it is a very complicated and effective structure. Consequently, human brain, with the abilities of learning, combining, adapting, generalizing etc., can be defined as excessively complicated nonlinear and a parallel distributed data processing system.

CHAPTER 3

ARTIFICIAL NEURAL NETWORK

Brains ascendant skills impress scientists to study on methodology of how to brain works. Some mathematical models for brain are created. However modeling every skill of brain is impossible. Only a few skills are limitedly created. To create truth model, understanding and modeling somatic components of brain truth is important then some various artificial neurons are improved (Sağıroğlu, 2003). Artificial neural network which is different from algorithmic calculation method of today's computers is developed as a new science area (Aslantaş and Kurban, 2007).

ANN is modeled as the result of inspiration from biological neural systems and it has much simpler structure comparing them. Many developed ANN systems imitate some well known characteristics of biological neural networks like learning capability. Some other features are developed using engineering approach instead of neural physiological approaches (Karlık, 2007).

ANN which can produce new outcomes, generate new information, discover new outputs by capability of learning, is new computer systems which has no need of any aid (Öztemel, 2003).

First studies related with ANN supplied by McCulloch and Pitts. They published an article which can be considered as the first step in ANN related researches (McCulloch and Pitts, 1943). First artificial neuron was developed by them. They pointed that every logical expression cab be formulated by artificial neuron.

Hebb (1949) improved a learning rule for an artificial neural network which is consisting of artificial neurons.

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The ANN looks at the learning samples, generalizes these samples and generates a learning rule from samples. ANN can decide a reason on any sample which is not seen before by using learning rules.

Our brain learns by regulating synaptic connections. Human starts learning by experiences when he was born. Brain is continuously developed. When the number of synaptic connections is increased, learning is come true. This rule is the same for the ANN. Learning is the relation of the input/output values and regulation of this relation by updating weights of the synapses.

ANN is mathematical system which is consisting of processing elements which are connected to each other. A processing element is a function generally called as activation function. A processing element takes inputs from others neurons, adds them and activation function calculate output from the added value. A processing element shortly can be thought as a neuron, connect each other and formed ANNs.

Our brain is composed of 10^{11} neuron cells that send electrical signal to each other. Each neuron has one or two axon and many dentrides. Axon works as output and dendrites work as input of electrical signals. Input signals add up from all the dendrites. If the sum is strength enough output is triggered, neuron fires and electrical signal send to other neurons by axon. Connections will strengthen if they are often used (Hagan et. al., 1995).

Neural Calculation has decentralized, nonlinear and adapted structure. ANN's calculation is different from traditional calculation methods. In traditional processor, a central processing element does every process one by one. But ANN has many simple processing elements. Every element is interested in any part of a problem. At first sight, it looks so simple. Neural calculation power comes from dense connection of processing elements which share load of total calculation. Artificial neurons settle as layers and fire activation function simultaneously. Nearly every layer has neurons which take inputs, produce outputs.

3.1 ARTIFICIAL NEURAL NETWORK FEATURES

ANN's strong calculation and processing ability comes from parallel decentralized architecture, learning and generalizing ability. Generalization is thought as generating suitable outputs for the inputs which is not known before. Because of this generalization ability, ANN can be used for complex problems. Nowadays ANN is used in many scientific areas.

3.1.1 Nonlinearity

Processing element of ANN which is the main part of the structure, is not linear. So ANN which consists of these processing elements is not linear too. This nonlinear structure includes the full system architecture. Because nonlinearity, ANN can be used for complex, nonlinear and undecipherable problems.

3.1.2 Learning

ANN is different from traditional approaches with learning ability which is the main structure of ANN. For learning operation inputs and output values or only input values must be known (provided) before. Learning set which consists of inputs and output values must contain enough sample. Learning can be described as process of adjusting weights which defines relation between inputs and outputs since reaching suitable weights (Sağıroğlu, 2003).

3.1.3 Generalizability

Through its powerful parallel distributed structure and the learning capability, a neural network can produce reasonable outputs for the inputs not participated in the

learning process. It can handle imperfect or incomplete data, and has the potential to be fault tolerant. That is very useful when analyzing the practical noisy data (Zhang, 2006).

ANN can produce desired output response for samples which is not used in the training phase. For example a trained ANN for recognizing character can produce correct character value for damaged inputs. A trained ANN can act same system for undefined inputs values which is not shown before.

3.1.4 Adaptivity

The neural network has a natural capability to adapt its knowledge to changes in the applied environment. It can be retained to deal with the changes even in a no stationary environment. That makes it a useful tool in adaptive pattern recognition, adaptive signal processing and adaptive control.

ANN updates weight values according changes of the problem which is studied on. In a word, A trained ANN, can be trained again fort the changes of the problem. If the changes are continuous, training can continue on real time. Because of adaptation feature, ANN can be used for effectively in areas like signal processing, system controls and system diagnosis.

3.1.5 Error Tolerance

ANN has a parallel structure consist of many processing element which connects each other. The knowledge is decentralized on the processing elements. So some errors on the connections or on the neurons do not break ANN system. ANN can produce truth values although it has some broken connections or neurons. Error toleration is so high because of parallel and decentralized structure.

3.1.6 VLSI Implement ability

The massive parallel structure of neural network make it well suited for implementation using very-large-scale-integrated (VLSI) technology to achieve fast computation tasks (Zhang, 2006). Parallel and decentralized structure increases the speed of producing response time because neurons can perform transactions simultaneously. ANN is chosen for real time application.

3.1.7 Simplicity of Analysis and Design

ANN model and structure of processing element are nearly same for all problems. For different applications ANN can be consist of standard neurons. Various applications can use same learning algorithms and theorems.

3.2 PERCEPTRON

Perceptron is the main processing unit of ANN**.** It was firstly designed by Rosenblatt to classify a pattern (Rosenblatt, 1958). The perceptron is the simplest type of neural network and it is typically used for classification. A perceptron has three main parts. These are synapses, adder, and activation function. (Efe and Kaynak, 2000). A basic perceptron is shown in Figure 3.1.

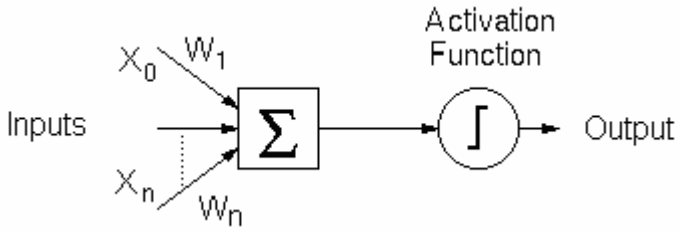


Figure 3.1. Perceptron (Dennis, 1997)

The synapses of the neuron are modeled as weights. The strength of the connection between an input and a neuron is noted by the value of the weight. Negative weight values reflect inhibitory connections, while positive values designate excitatory connections (Haykin, 1994). Inputs are multiplied by weights. An adder sums up all the weighted inputs. Activation function is applied to the result and net output is calculated. An acceptable range of output is usually between 0 and 1, or -1 and 1. Generally activation function is a nonlinear function.

3.3 ACTIVATION FUNCTION

Activation function is a simple on-off mechanism to determine whether or not a neuron fires(Haykin, 1998). Activation functions can be shown at Figure 3.2.

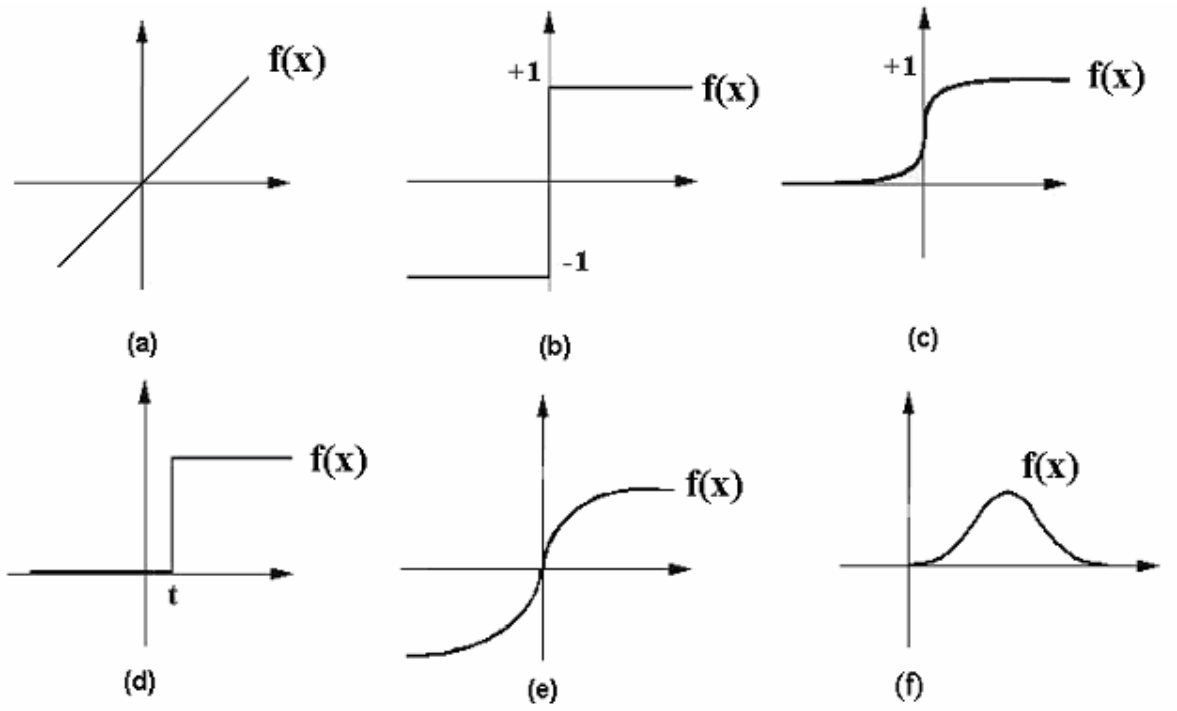


Figure 3.2 Basic activation functions (Kendall, 2008)
(a)Linear (b)Sign (c)Sigmoid (d)Step (e)Tanh (f)Gaussian

Activation functions are needed to introduce nonlinearity into the network. The sigmoid functions such as tanh and gaussian function are the most common choices. Sigmoid activation functions are usually preferable to threshold activation functions. With sigmoid units, a small change in the weights will usually produce a change in the outputs, which makes it possible to tell whether that change in the weights is good or bad. With threshold units, a small change in the weights will often produce no change in the outputs (McCullagh and Nelder, 1989).

3.4 MULTILAYERED PERCEPTRON (MLP)

A single perceptron is not very useful because of its limited mapping ability. No matter what activation function is used, the perceptron is only able to represent an oriented ridge-like function. The perceptrons can, however, be used as building blocks of a larger, much more practical structure. A typical network consists of a set of source nodes forming the input layer, one or more hidden layers of computation nodes, and an output layer of nodes. The input signal propagates through the network layer-by-layer.(Haykin, 1998)

The activity of the input units represents the raw information that is fed into the network (Aleksander and Morton, 1989) therefore it is not a computing layer since it has no weights and activation functions(Efe and Kaynak, 2000). Input layer transfers signals from the external environment to the hidden layer. The number of neurons in the input layer depends on the number of possible inputs.

The activity of each hidden unit is determined by weights on the connections between the input and the hidden units. There is no limit on the number of hidden layers but one or two hidden layer are enough for many problem and three hidden layer can solve problems of any complexity. Network can learn more complex patterns by adding of hidden layer. The number of hidden layers and number of neurons in each hidden layer is not well defined. The number of nodes in the hidden layer is generally set to the greater number of nodes in the output or input layer.

The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units. The number of neurons in the output layer depends on the number of desired outputs.

3.5 LEARNING ALGORITHMS

Learning is updating weights to reach desired outputs. ANN learns by sample of sets which contains input-output sets or only input sets. These sets are termed as learning set. Learning set must contains sufficient sample (Sağıroğlu, 2003).

Networks also don't converge if there is not enough data to enable complete learning. There are two major learning paradigms. These are supervised learning and unsupervised learning.

In unsupervised learning, the network is provided with inputs but not with desired outputs. unsupervised learning usually performs the same task as an auto-associative network, compressing the information from the inputs (Deco and Obradovic, 1996). The system itself must decide what features it will use to group the input data. This is often referred to as self-organization or adaption. unsupervised learning is very useful for data visualization (Ripley, 1996)

3.6 ANN MODELS

ANN can be modeled as feed forward and feedback networks. In feed forward model, outputs of a layer are given as inputs to next layer (Özbay and Karlık 2001). Nodes are connected to other layers but they are not connected to nodes in the same layer. Input layer transmits data from external environment to the hidden layer. In hidden layer input data is processed and output of ANN is generated.

3.6.1 Feed-Forward Networks

In feed-forward networks previous perceptron output can be used as next perceptron input. Perceptrons are arranged in layers, with the first layer taking in inputs and the last layer producing outputs. The middle layers have no connection with the external world, and called as hidden layers. Each perceptron in one layer is connected to every perceptron on the next layer. Information is feed forward from one layer to the next. Feed forward is shown in Figure 3.3.

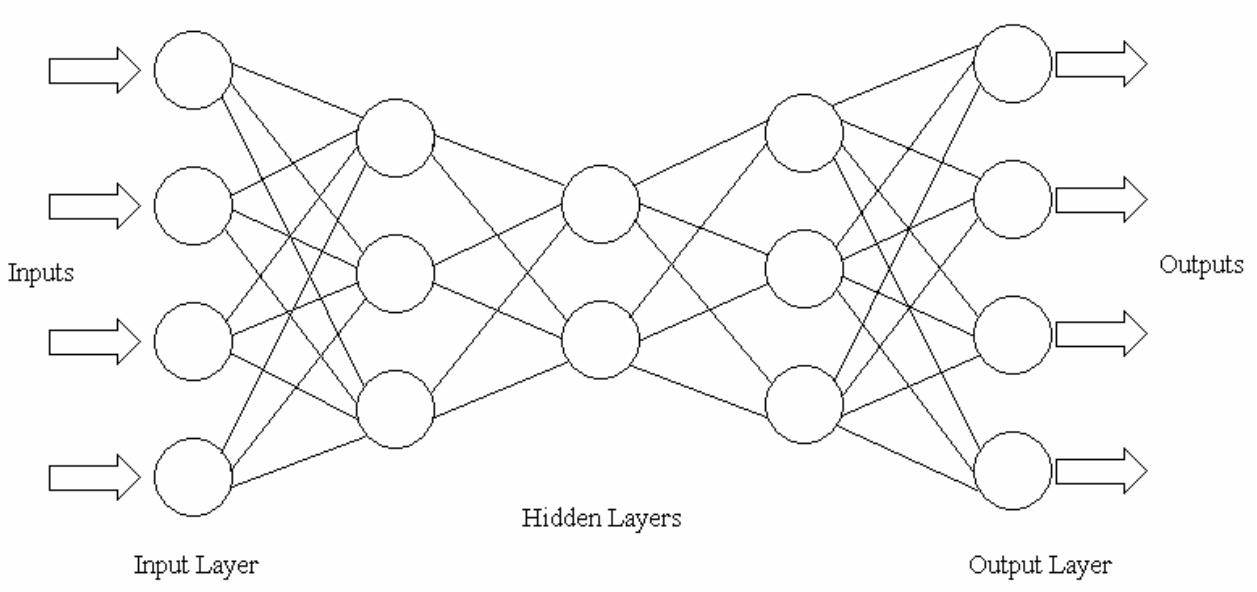


Figure 3.3. Feed-Forward Network (Stanford CSE, 2008)

Feed-forward networks are the fastest models to execute. Multilayer feed-forward networks should be chosen if rapid execution rates are required,

The number of hidden nodes and training iterations is also impotent. Too few hidden nodes, and the network will be unable to learn a given tasks; too many, and its generalization will be poor. Too few training iterations, and the network will be unable to extract important features from the training set; too many, and the net will begin to learn the details of the training set as noise (Masters, 1993).

The best-known and simplest training algorithm for feed-forward network is backpropagation (Rumelhart et al., 1986).

3.6.1.1 Backpropogation

Back Propagation (Rumelhart et al., 1986) is the network training method of choice for many neural network projects, and for good reason. It is a supervised learning algorithm to change the weights connected to the net's hidden neuron layer(s). The backpropagation algorithm uses a computer output error which is propagated through the network in the backward direction, hence the name of the algorithm to change the weight values (haykin,1999)

Multilayered feed-forward networks have a better ability to learn the correspondence between input patterns and teaching values from many sample data by the error back-propagation algorithm (Rumerhalt, 1986).

The backpropagation algorithm looks for the minimum of the error function in weight space using the method of gradient descent. The combination of weights which minimizes the error function is considered to be a solution of the learning problem. Since this method requires computation of the gradient of the error function at each iteration step, the continuity and differentiability of the error function must be guaranteed. One of the more popular activation functions for backpropagation networks is the sigmoid (Rojas, 1996).

$$s(x) = \frac{1}{1+e^{-x}} \tag{3.1}$$

Algorithm starts feeding the input data to first layer with small randomly selected weights. From node i to node j net input is calculated as below.

net_i : Net input to unit i

w_{ij} : Connection strength from unit i to unit j

a_i : Activation of unit i

$$net_i = \sum_{\forall j w_{ji} \neq 0} w_{ij} * x_j \tag{3.2}$$

$$a_i = \frac{1}{1 + e^{-net_i}} \tag{3.3}$$

E_p : Quadratic error for pattern p

o_i : Desired activation of output unit i

$$E_p = \sum \left(a_i - o_i\right)^2 \tag{3.4}$$

E : Total quadratic error on the training set

$$E = \sum_p E_p \tag{3.5}$$

$\frac{\partial E_p}{\partial w_{ij}}$: Partial derivative for pattern p with respect to w_{ij}

$\frac{\partial E}{\partial w_{ij}}$: Partial derivative for the whole training set with respect to w_{ij}

$$\frac{\partial E}{\partial w_{ij}} = \sum_p \frac{\partial E_p}{\partial w_{ij}} \tag{3.6}$$

∇E : Gradient with respect to the whole trainings set

$$\nabla E = \left(\frac{\partial E}{\partial w_1}, \frac{\partial E}{\partial w_2}, ..., \frac{\partial E}{\partial w_n}, \right) \tag{3.7}$$

∇E_p : Gradient with respect to pattern p

$$\nabla E_p = \left(\frac{\partial E_p}{\partial w_1}, \frac{\partial E_p}{\partial w_2}, ..., \frac{\partial E_p}{\partial w_n}, \right) \tag{3.8}$$

$\Delta w_{ij}(n)$: Weight update of w_{ij} in the n-th learning step

$$w_{ij}(n+1) = \Delta w_{ij}(n) + w_{ij}(n) \tag{3.9}$$

Basically, backpropagation (Rumelhart, 1986) is a gradient descent technique to minimize some error criteria E . In the batched mode variant the descent is based on the gradient ∇E for the total training set:

$$\Delta w_{ij}(n) = -\varepsilon * \frac{\partial E}{\partial w_{ij}} + \alpha * \Delta w_{ij}(n-1) \tag{3.10}$$

ε and α are two non negative constant parameters called learning rate and momentum. The momentum can speed up training in very flat regions of the error surface and suppresses weight oscillation in step valleys or ravines. Unfortunately it is necessary propagate the whole training set through the network for calculating ∇E . This can slow down training for bigger training sets. For some tasks (e.g. neural controllers) no finite training set is available. Therefore the update is based just on the gradient for the actual training pattern ∇E (Schiffmann et. al., 1993):

$$\Delta w_{ij}(n) = -\varepsilon * \frac{\partial E_p}{\partial w_{ij}} + \alpha * \Delta w_{ij}(n-1) \tag{3.11}$$

3.6.1.2 Training a Neural Network Using Backpropagation

The triple layer neural network with two inputs and one output is illustrated at Figure 3.4.

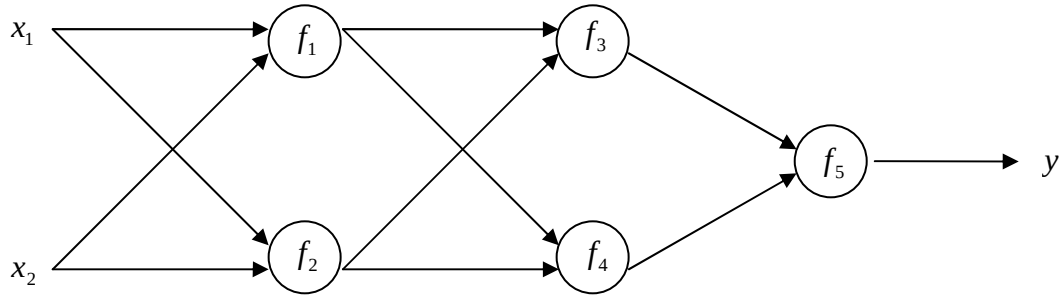


Figure 3.4 Triple Layer Network

Training data set is needed for training phase. The training data set consists of input signals and output signal. The network training is an iterative process. In each iteration weights are updated. Each teaching step includes feeding input signals to network from training set. After this step output signal value is determined for each neuron in each network layer. Calculation of a neuron output is shown at Figure 3.5.

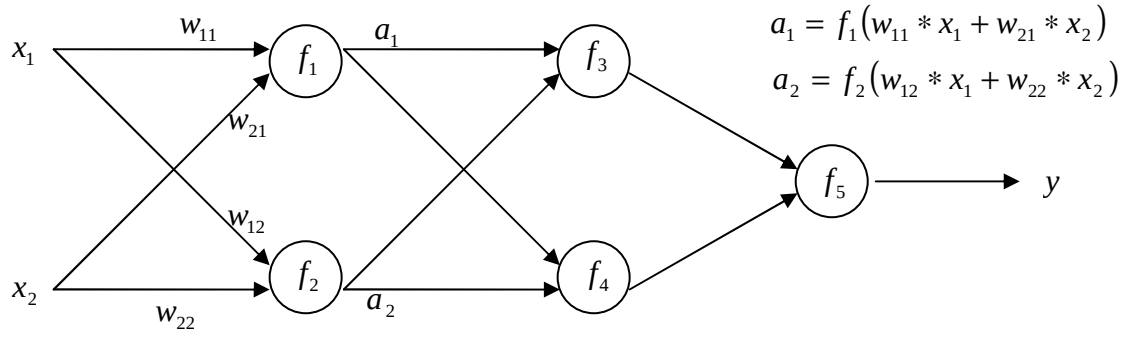


Figure 3.5 Calculation of a neuron output

$$net_1 = \sum w_{i1} * x_j \tag{3.12}$$

$$net_1 = w_{11} * x_1 + w_{21} * x_2 \tag{3.13}$$

$$a_1 = f_1(net_1) \tag{3.14}$$

$$a_1 = f_1(w_{11} * x_1 + w_{21} * x_2) \tag{3.15}$$

$$a_2 = f_2(w_{12} * x_1 + w_{22} * x_2) \tag{3.16}$$

values are calculated for hidden layer at Figure 3.6.

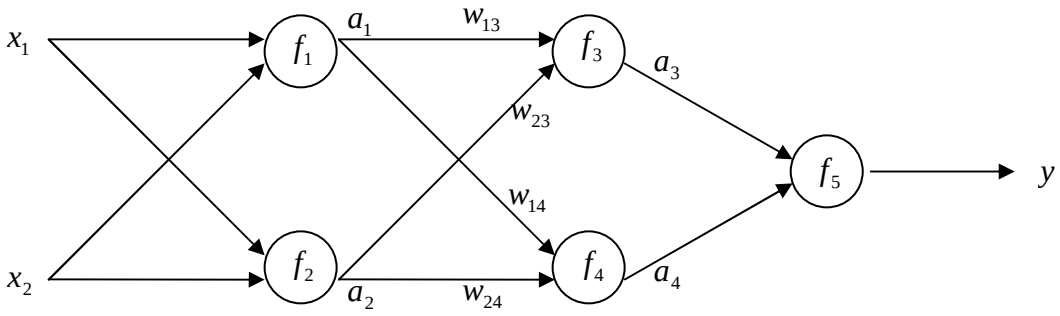


Figure 3.6 Neuron output at hidden layer

$$a_3 = f_3(w_{13} * a_1 + w_{23} * a_2) \tag{3.17}$$

$$a_4 = f_4(w_{14} * a_1 + w_{24} * a_2) \tag{3.18}$$

System output is calculated is shown at Figure 3.7. (Propagation of signals through the output layer.):

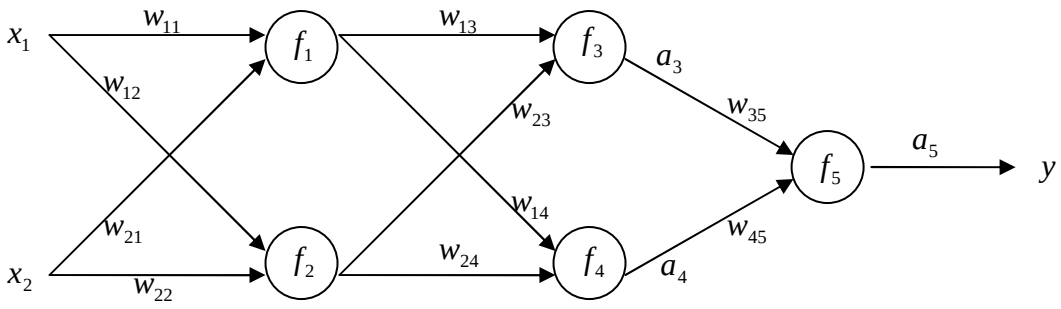


Figure 3.7 Calculated Output

$$a_5 = f_5\left(w_{35} * a_3 + w_{45} * a_4\right) \tag{3.19}$$

$$y = a_5 \tag{3.20}$$

In the next algorithm step the output signal of the network y, which is found in training data set, is compared with the desired output value (the target) z. The difference is called error signal δ. Backpropogation of the error is shown at Figure 3.8.

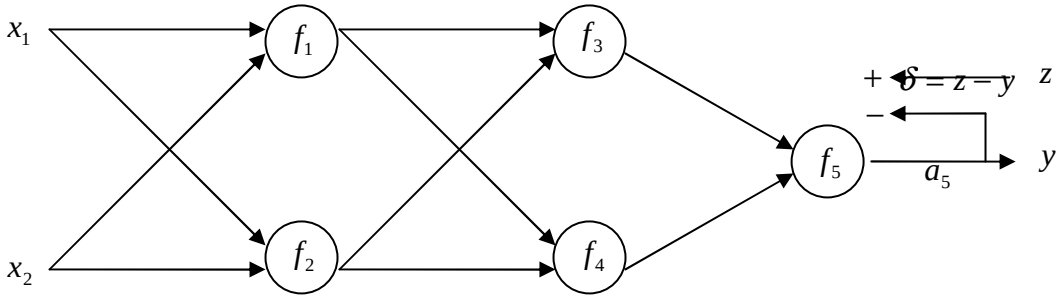


Figure 3.8. Backpropogation of the error

$$\delta = z - y$$

Error signal δ is propagated back to all neurons. This step is illustrated at Figure 3.9.

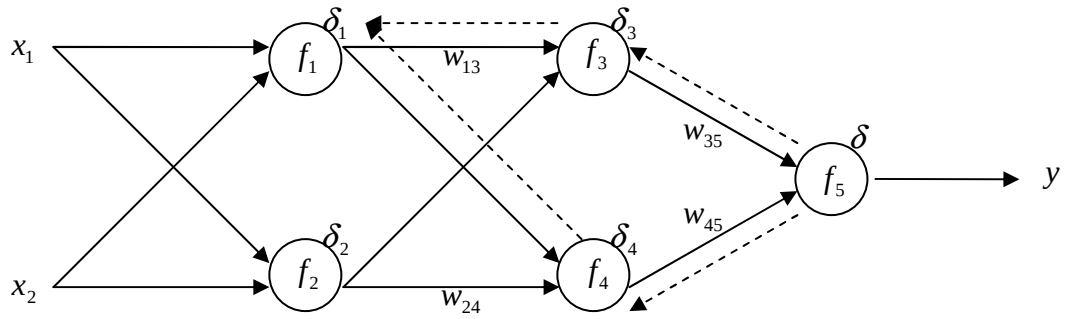


Figure 3.9 Illustration of backpropogation

$$\delta_4 = w_{45} * \delta \tag{3.21}$$

$$\delta_3 = w_{35} * \delta \tag{3.22}$$

$$\delta_2 = w_{23} * \delta_3 + w_{14} * \delta_4 \tag{3.23}$$

$$\delta_1 = w_{13} * \delta_3 + w_{14} * \delta_4 \tag{3.24}$$

Calculated new weights are illustrated at Figure 3.10.

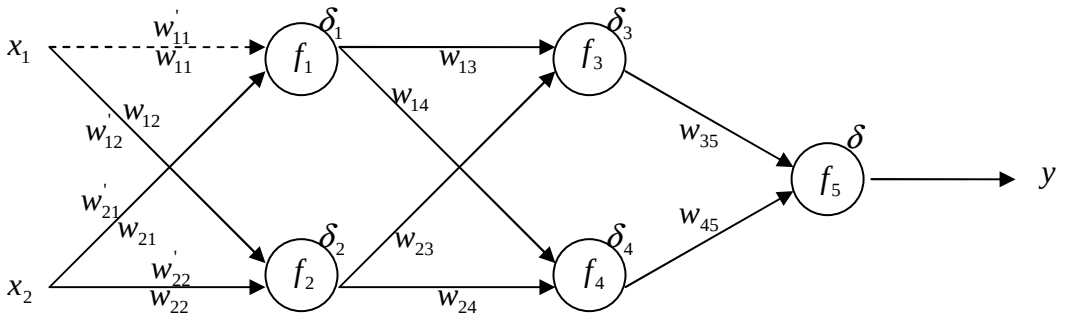


Figure 3.10 Calculation of new weights

$$w'_{11} = \Delta w_{11} + w_{11} \tag{3.25}$$

$$w_{11}^{'} = \eta\delta_1 \frac{\partial f_1(x)}{\partial x} x_1 + w_{11} \tag{3.26}$$

$$w_{12}^{'} = \eta\delta_2 \frac{\partial f_2(x)}{\partial x} x_1 + w_{12} \tag{3.27}$$

$$w_{21}^{'} = \eta\delta_1 \frac{\partial f_1(x)}{\partial x} x_2 + w_{21} \tag{3.28}$$

$$w_{22}^{'} = \eta\delta_2 \frac{\partial f_2(x)}{\partial x} x_2 + w_{22} \tag{3.29}$$

3.6.2 Hopfield Networks

A Hopfield net is a form of recurrent artificial neural network invented by John Hopfield. Hopfield net is a recurrent neural network having synaptic connection. Started in any initial state, the state of the system evolves to a final state that is a local minimum. They are guaranteed to converge to a local minimum, but convergence to one of the stored patterns is not guaranteed (Hopfield, 1982). Hopfield network is shown at Figure 3.11.

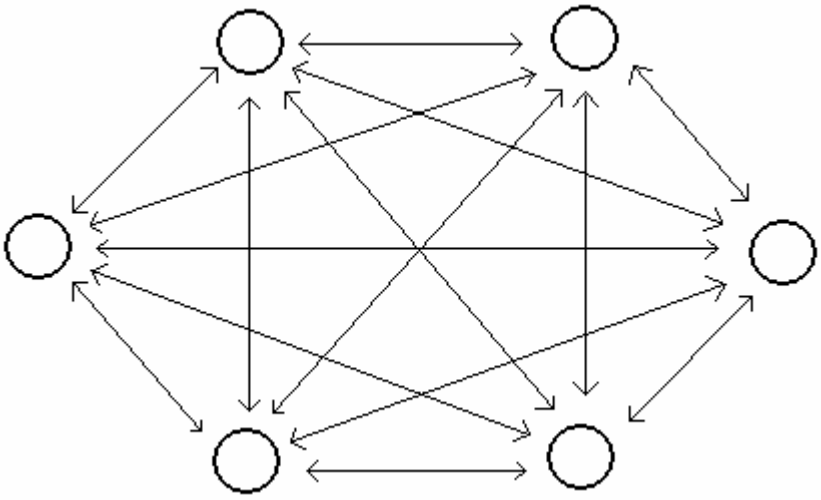


Figure 3.11 Hopfield Network (Elmas, 2003)

Hopfield network forms as circular system. Also processing unit in the same layer connects each other.

3.6.3 Self-Organizing Map (SOM)

Self-Organizing Map (SOM), with its variants, is the most popular artificial neural network algorithm in the unsupervised learning category. Self-Organizing Map (SOM), is an algorithm used to visualize and interpret large high-dimensional data sets. Typical applications are visualization of process states or financial results by representing the central dependencies within the data on the map (Kohenan, 1998).

The SOM first introduced by Kohonen, is an unsupervised (self-organizing) neural network composed of an input layer and a competitive/output neural layer. The SOM solves difficult nonlinear and high-dimensional problems such as feature extraction and classification of images and acoustic patterns, adaptive control of robots, and equalization, demodulation, and error-tolerant transmission of signals in telecommunications. A new area is the organization of very large document collections (Kohenan,2001).

SOMs are used in many field of science as statistics, signal processing, control theory, financial analysis, experimental physics, chemistry and medicine.

Teuvo Kohonen writes "The SOM is a new, effective software tool for the visualization of high-dimensional data. It converts complex, nonlinear statistical relationships between high-dimensional data items into simple geometric relationships on a low-dimensional display. As it thereby compresses information while preserving the most important topological and metric relationships of the primary data items on the display, it may also be thought to produce some kind of abstractions." (Koohen,2001).

3.6.4 Learning Vector Quantization

Vector quantization is one example of competitive learning. The goal here is to have the network "discover" structure in the data by finding how the data is clustered. The results can be used for data encoding and compression. One such method for doing this is called vector quantization (Willamette, 2008). An example of vector quantization can be shown at Figure 3.14.

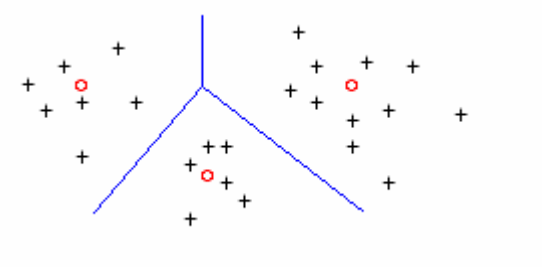


Figure 3.14 Vector Quantization (Willamette, 2008)

Learning Vector Quantization (LVQ) is a supervised version of vector quantization. Classes are predefined.

3.6.4.1 The LVQ Approach

The basic LVQ approach is quite intuitive. It is based on a standard trained SOM with input vectors {x} and weights/Voronoi vectors {wj}. The new factor is that the input data points have associated class information. This allows us to use the known classification labels of the inputs to find the best classification label for each wj, i.e. for each Voronoi cell. For example, by simply counting up the total number of instances of each class for the inputs within each cell. Then each new input without a class label can be assigned to the class of the Voronoi cell it falls within. The problem with this is that, in general, it is unlikely that the Voronoi cell boundaries will match up with the best possible classification boundaries, so the classification generalization performance will not be as

good as possible. The obvious solution is to shift the Voronoi cell boundaries so they better match the classification boundaries (Bullinaria, 2007).

3.6.4.2 The LVQ Algorithm

The basic LVQ algorithm is a straightforward method for shifting the Voronoi cell boundaries to result in better classification. It starts from the trained SOM with input vectors $\{x\}$ and weights/Voronoi vectors $\{w_j\}$, and uses the classification labels of the inputs to find the best classification label for each w_j. The LVQ algorithm then checks the input classes against the Voronoi cell classes and moves the w_j appropriately (Bullinaria, 2007):

If the input x and the associated Voronoi vector/weight $w_{I(x)}$ (i.e. the weight of the winning output node $I(x)$) have the same class label, then move them closer together by $\Delta w_{I(x)}(t) = \beta(t)(x - w_{I(x)}(t))$ as in the SOM algorithm.

If the input x and associated Voronoi vector/weight $w_{I(x)}$ have the different class labels, then move them apart by $\Delta w_{I(x)}(t) = -\beta(t)(x - w_{I(x)}(t)$.

Voronoi vectors/weights wj corresponding to other input regions are left unchanged with $w_{J(x)}(t)$ = 0. where $\beta(t)$ is a learning rate that decreases with the number of iterations/epochs of training.

3.6.5 Elman Network

Elman has proposed a partially recurrent network, where the feedforward connections are modifiable as shown in Figure 3.15. The Elman network is a two-layer network with feedback from the first layer output to the first layer input. This recurrent connection allows the Elman network to both detect and generate time-varying patterns (Mahamad et al., 2007).

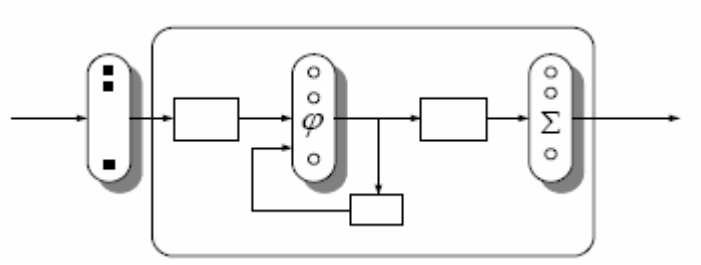


Figure 3.15 Block diagram of Elman network (Mahamad et al., 2007)

Elman network is preferred because it exhibits dynamic behavior. In order to select an optimum network it can be chosen by trial and error, started with on two hidden nodes until twenty hidden nodes together with and Elman Network until the optimum network obtained. The selection corresponds based on the smallest cross validation errors produced (Mahamad et al., 2007).

CHAPTER 4

MAGNETIC RESONANCE IMAGING (MRI)

Magnetic resonance imaging (MRI), or nuclear magnetic resonance imaging (NMRI), is primarily a medical imaging technique most commonly used in radiology to visualize the structure and function of the body. It provides detailed images of the body in any plane. MRI provides much greater contrast between the different soft tissues of the body than computed tomography (CT) does, making it especially useful in neurological (brain), musculoskeletal, cardiovascular, and oncological (cancer) imaging. Unlike CT, it uses no ionizing radiation, but uses a powerful magnetic field to align the nuclear magnetization of (usually) hydrogen atoms in water in the body. Radiofrequency fields are used to systematically alter the alignment of this magnetization, causing the hydrogen nuclei to produce a rotating magnetic field detectable by the scanner. This signal can be manipulated by additional magnetic fields to build up enough information to construct an image of the body. MRI is an imaging system which can scan internal organ and tissues in detail without using X-rays. MR is not harmful for bodies, because the system does not use X rays. So, it can be used on babies and pregnant (Haacke et al., 1999).

4.1 Brief lay explanation of MRI physics

Magnetic resonance imaging was developed from knowledge gained in the study of nuclear magnetic resonance. In its early years the technique was referred to as nuclear magnetic resonance imaging (NMRI). However, as the word *nuclear* was associated in the public mind with ionizing radiation exposure it is generally now referred to simply as MRI.

Scientists still use the term NMRI when discussing non-medical devices operating on the same principles. The term Magnetic Resonance Tomography (MRT) is also sometimes used MR is the best method of the radiological diagnosis systems in differentiating tissues (Çavdaroğlu, 2006 and Tuncel, 2004).

The body is mainly composed of water molecules which each contain two hydrogen nuclei or protons. When a person goes inside the powerful magnetic field of the scanner these protons align with the direction of the field. A second radiofrequency electromagnetic field is then briefly turned on causing the protons to absorb some of its energy. When this field is turned off the protons release this energy at a radiofrequency which can be detected by the scanner. The position of protons in the body can be determined by applying additional magnetic fields during the scan which allows an image of the body to be built up. These are created by turning gradients coils on and off which creates the knocking sounds heard during an MR scan. Figure 4.1 shows the effect of magnetic field on the movements of protons. In Figure 4.1.a protons move randomly before magnetic field is enforced. In Figure 4.1.b., after the magnetic field is enforced protons move in the same or opposite direction of the magnetic field (Çavdaroğlu, 2006).

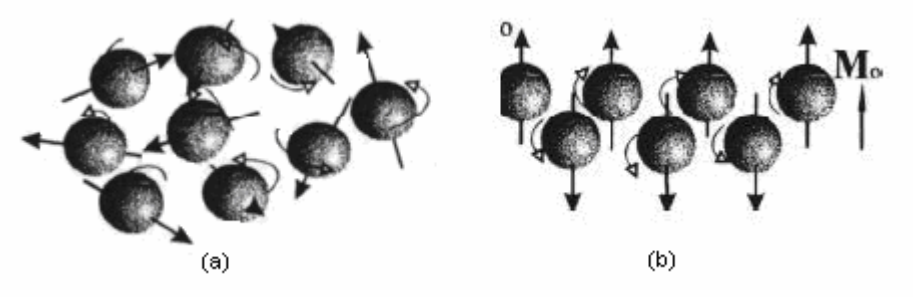


Figure 4.1 Protons movement (Çavdaroğlu, 2006).

In the nucleus of atom the rotation of proton around itself generates a magnetic field. Hydrogen atom has a single proton and so, it has a strong magnetic field (Çavdaroglu, 2006). A big proportion of human body consists of water (H_2O) which contains two hydrogen atoms. Because of these hydrogen protons are randomly placed in human body, magnetization in the body is zero. But when a part of the body which will be examined,

placed into a strong magnetic field, protons locate parallel to magnetic field vector. In this position protons wobble back and forth. While protons are wobbling if they are stimulated by radio waves, then they move from their original position and make an angle with magnetic field vector. When the radio waves are turned off, protons revert to their original position. In this process protons, as a result of their vibrations, disperse a signal. MR images are created by measuring these signals (Koca, 2007).

A number of schemes have been devised for combining field gradients and radiofrequency excitation to create an image. One involves 2D or 3D reconstruction from projections, much as in Computed Tomography. Others involve building the image point-by-point or line-by-line. One even uses gradients in the rf field rather than the static field. Although each of these schemes is occasionally used in specialist applications, the majority of MR Images today are created either by the Two-Dimensional Fourier Transform (2DFT) technique with slice selection, or by the Three-Dimensional Fourier Transform (3DFT) technique. Another name for 2DFT is spin-warp. What follows here is a description of the 2DFT technique with slice selection. Slice selection is achieved by applying a magnetic gradient in addition to the external magnetic field during the radio frequency pulse. Only one plane within the object will have protons that are on–resonance and contribute to the signal.

A real image can be considered as being composed of a number of spatial frequencies at different orientations. A two–dimensional Fourier transformation of a real image will express these waves as a matrix of spatial frequencies known as k–space. Low spatial frequencies are represented at the center of k–space and high spatial frequencies at the periphery. Frequency and phase encoding are used to measure the amplitudes of a range of spatial frequencies within the object being imaged. The frequency encoding gradient is applied during readout of the signal and is orthogonal to the slice selection gradient. During application of the gradient the frequency differences in the readout direction progressively change. At the midpoint of the readout these differences are small and the low spatial frequencies in the image are sampled filling the center of k-space. Higher spatial frequencies will be sampled towards the beginning and end of the readout filling the periphery of k-space.

Phase encoding is applied in the remaining orthogonal plane and uses the same principle of sampling the object for different spatial frequencies. However, it is applied for a brief period before the readout and the strength of the gradient is changed incrementally between each radio frequency pulse. For each phase encoding step a line of k–space is filled. Either a spin echo or a gradient echo can be used to refocus the magnetisation.

The 3DFT technique is rather similar except that there is no slice selection and phase-encoding is performed two separate directions. Another scheme which is sometimes used, especially in brain scanning or where images are needed very rapidly, is called echo-planar imaging (EPI): in this case each rf excitation is followed by a whole train of gradient echoes with different spatial encoding (Ljunggren, 1983; Twieg, 1983).

4. 2 IMAGE CONTRAST AND CONTRAST ENHANCEMENT

Contrast agents may be injected intravenously to enhance the appearance of blood vessels, tumors or inflammation. Contrast agents may also be directly injected into a joint, in the case of arthrograms, MR images of joints. Unlike CT scanning MRI uses no ionizing radiation and is generally a very safe procedure. Patients with some metal implants, cochlear implants, and cardiac pacemakers are prevented from having an MRI scan due to effects of the strong magnetic field and powerful radiofrequency pulses (Widder, 1987).

Image contrast is created by differences in the strength of the NMR signal recovered from different locations within the sample. This depends upon the relative density of excited nuclei (usually water protons), on differences in relaxation times (T_1, T_2 and T_2 *) of those nuclei after the pulse sequence, and often on other parameters discussed under specialized MR scans. Contrast in most MR images is actually a mixture of all these effects, but careful design of the imaging pulse sequence allows one contrast mechanism to be emphasized while the others are minimized. The ability to choose different contrast mechanisms gives MRI tremendous flexibility. In the brain, T_1-weighting causes the nerve

connections of white matter to appear white, and the congregations of neurons of gray matter to appear gray, while cerebrospinal fluid (CSF) appears dark. The contrast of white matter, gray matter and cerebrospinal fluid is reversed using T_2 or T_2 * imaging, whereas proton-density-weighted imaging provides little contrast in healthy subjects. Additionally, functional parameters such as cerebral blood flow (CBF), cerebral blood volume (CBV) or blood oxygenation can affect T_1, T_2 and T_2 * and so can be encoded with suitable pulse sequences (Weisleder et al., 1990).

In some situations it is not possible to generate enough image contrast to adequately show the anatomy or pathology of interest by adjusting the imaging parameters alone, in which case a contrast agent may be administered. This can be as simple as water, taken orally, for imaging the stomach and small bowel. However, most contrast agents used in MRI are selected for their specific magnetic properties.

MRI is used to image every part of the body, and is particularly useful in neurological conditions, disorders of the muscles and joints, for evaluating tumors and showing abnormalities in the heart and blood vessels. Diseased tissue, such as tumors, can be detected because the protons in different tissues return to their equilibrium state at different rates. By changing the parameters on the scanner this effect is used to create contrast between different types of body tissue.

4. 3 ECONOMICS AND SAFETY OF MRI

MRI equipment is expensive. 1.5 tesla scanners often cost between $1 million and $1.5 million USD. 3.0 tesla scanners often cost between $2 million and $2.3 million USD. Construction of MRI suites can cost up to $500,000 USD, or more, depending on project scope. MRI scanners have been significant sources of revenue for healthcare providers in the US. This is because of favorable reimbursement rates from insurers and federal government programs. Insurance reimbursement is provided in two components, an equipment charge for the actual performance of the MRI scan and professional charge for the radiologist's review of the images and/or data. In the US Northeast, an equipment

charge might be $3,500 and a professional charge might be $350. Some insurance companies require preapproval of an MRI procedure as a condition for coverage. In the US, the 2007 Deficit Reduction Act (DRA) significantly reduced reimbursement rates paid by federal insurance programs for the equipment component of many scans, shifting the economic landscape (Stamford CT US, 2008).

Pacemakers are generally considered an absolute contraindication towards MRI scanning, though highly specialized protocols have been developed to permit scanning of select pacing devices. Several cases of arrhythmia or death have been reported in patients with pacemakers who have undergone MRI scanning without appropriate precautions. Notably, the Medtronic company has received FDA approval for the first-ever clinical trial for a MR-Conditional pacemaker device, which has already received regulatory approval in Europe. Other electronic implants have varying contraindications, depending upon scanner technology, and implant properties, scanning protocols and anatomy being imaged.Many other forms of medical or biostimulation implants may be contraindicated for MRI scans. These may include vagus nerve stimulators, implantable cardioverter-defibrillators, loop recorders, insulin pumps, cochlear implants, deep brain stimulators, and many others. Medical device patients should always present complete information (manufacturer, model, serial number and date of implantation) about all implants to both the referring physician and to the radiologist or technologist before entering the room for the MRI scan. While these implants pose a current problem, scientists and manufacturers are working on improved designs which will further minimize the risks that MRI scans pose to medical device operations. One such development in the works is a nano-coating for implants intended to screen them from the radio frequency waves, helping to make MRI exams available to patients currently prohibited from receiving them. The current article for this is from New Scientist (Price et al., 2001; The Open University, 2007).

Ferromagnetic foreign bodies (e.g. shell fragments), or metallic implants (e.g. surgical prostheses, aneurysm clips) are also potential risks, and safety aspects need to be considered on an individual basis. Interaction of the magnetic and radio frequency fields with such objects can lead to: trauma due to movement of the object in the magnetic field,

thermal injury from radio-frequency induction heating of the object, or failure of an implanted device. These issues are especially problematic when dealing with the eye. Most MRI centers require an orbital x-ray to be performed on anyone suspected of having metal fragments in their eyes, something not uncommon in metalworking. Because of its non-ferromagnetic nature and poor electrical conductivity, titanium and its alloys are useful for long term implants and surgical instruments intended for use in image-guided surgery. In particular, not only is titanium safe from movement from the magnetic field, but artifacts around the implant are less frequent and less severe than with more ferromagnetic materials e.g. stainless steel. Artifacts from metal frequently appear as regions of empty space around the implant - frequently called 'black-hole artifact' e.g. a 3mm titanium alloy coronary stent may appear as a 5mm diameter region of empty space on MRI, whereas around a stainless steel stent, the artifact may extend for 10-20 mm or more (Donald and McNeil, 2005). As far as is known, there is no harmful effect of MR on human bodies. A little medicine can be given to the body from vein for better diagnosis of healthy and unhealthy regions. Depending on the amount of contained water, any information about certain regions can be obtained by MR. MR can be used for the determination of the existence of mass (Kanal et al., 2007; Acr Org, 2007).

CHAPTER 5

BRAIN DISEASES

The brain is the control center and the most complex part of the body. The brain consists of billions of cells called neurons.

The symptoms of brain diseases are depending on damages, treatments such as surgery, medicines or physical therapy. Brain tumors can press on nerves and affect brain function. Loss of brain cells can affect ability of living.

5.1 Tumor

A brain tumor is created by abnormal and uncontrolled cell division. It is a mass or growth of abnormal cells in brain. Brain tumors begin when normal cells acquire errors (mutations) in their DNA. These mutations allow cells to grow and divide at increased rates and to continue living when healthy cells would die. The result is a mass of abnormal cells, which forms a tumor. Some brain tumors are noncancerous, and some brain tumors are cancerous.

Tumors can directly destroy brain cells and indirectly damage cells by producing inflammation, compressing other parts of the brain as the tumor grows, causing swelling in the brain, and increasing pressure within the skull. The tumor can deform brain structure.

Headaches, weakness in one part of the body, and changes in the person's mental functions are most common symptoms depends on the tumor's size, location, degree of invasion, and related swelling.

Computed Tomography (CT) or MRI can help about brain tumor. MR Images of tumor are shown in Figure 5.1.

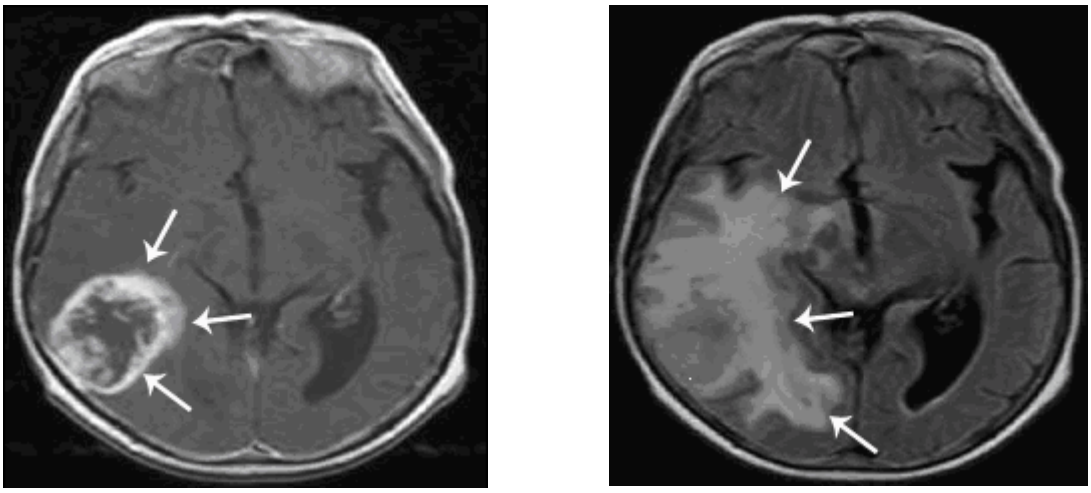


Figure 5.1 Sample MR images of tumor used in the study

5.2 MENINGITIS

Meningitis is inflammation of the meninges, the lining surrounding the brain and the spinal cord. It can be caused by many different organisms including bacteria, viruses and fungi. Bacterial meningitis in the pediatric population is comprised of three microorganisms in more than 95% of cases: S. pneumoniae, N. meningitides and H. influenza type B. Acute bacterial meningitis is fairly uncommon, but it is the most dangerous infection in normal host. It can be extremely serious, as it is fatal in one in 10 cases; one in seven survivors is left with severe handicap, such as deafness or brain injury. Although fever, headache, vomiting, stiff neck, and meningeal irritation findings are highly suggestive of meningitis, the definite diagnosis must be based on Cerebrospinal Fluid (CSF) examination. Early diagnosis and prompt treatment are essential in avoiding the complications of this serious infection in the childhood. (Kanra et al., 2003).

Meningitis is an inflammation of the membranes and cerebrospinal fluid surrounding brain and spinal cord, usually due to the spread of an infection. The swelling associated with meningitis often triggers headache, fever and a stiff neck. MR images of meningitis are shown at Figure 5.2.

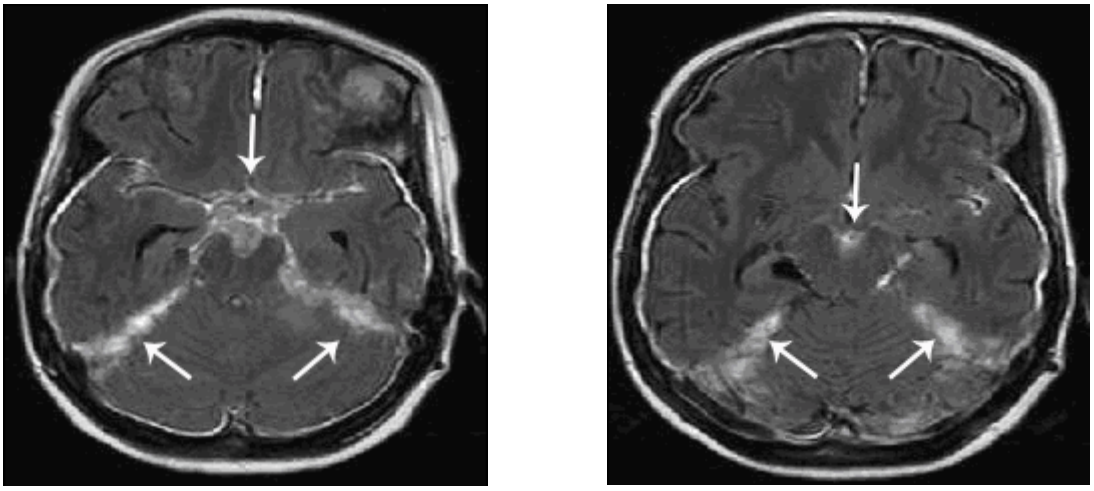


Figure 5.2 Sample MR images of meningitis used in the study

5.3 SEIZURE

A seizure can be described as sudden change in behavior due to an excessive electrical activity in the brain.

The most common cause of seizures is cerebrovascular disease in elderly population. Late onset seizures are not investigated as well as early onset seizures in patients with stroke. There is no common consensus about clinical, electrophysiological and radiological features of these seizures (Göksel et.al., 2005).

There are two types of partial seizures: Simple partial seizures, which don’t cause unconsciousness and complex partial seizures, which do cause loss of consciousness. Simple partial seizures commonly cause convulsive jerking or twitching (if the frontal lobe is involved), tingling or numbness (if the parietal lobe is involved) or other unusual sensations. These symptoms can begin in one part of the body and then spread to other

areas. Chewing movements or lip smacking (if the anterior temporal lobe is involved), buzzing in the ears, flashes of lights, sweating, and flushing and pupil dilation are other common symptoms. Psychic symptoms include a sense of déjà vu, imaginary sights (if the occipital lobe is involved), smells (if the temporal lobe is involved) or tastes, or imaginary sounds. Complex partial seizures cause some loss of consciousness and usually indicate temporal lobe involvement. Purposeless, automatic movements might occur. The seizure may be preceded, accompanied by, or followed by psychic symptoms. A state of confusion may last for a time after the attack. In patients with low-grade gliomas, this is the most common type of seizure (Luhdorf et. al., 1986).

Alcohol withdrawal, metabolic factors, toxins, drugs, sleep deprivation and acute infection or trauma may trigger seizures. These can occur without or with predisposition to a seizure. The Driver and Vehicle Licensing Agency (DVLA) definition of ‘provoked’ seizure differs and refers to an ‘exceptional circumstance’ which is unlikely to recur, such as a seizure at the time of a head injury. Sometimes the imposed driving restriction is less. It does not include seizures related to alcohol, recreational or other drugs (Angus-Leppan and Persons,2008). MR image of seizure is shown at Figure 5.3.

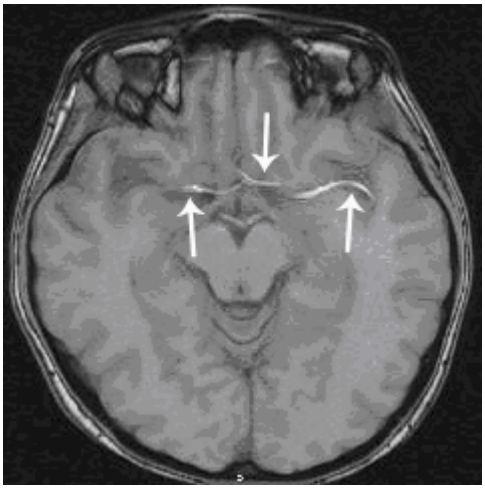


Figure 5.3 Sample MR image of seizure used in the study

CHAPTER 6

DIAGNOSIS OF TUMOR, MENINGITIS AND SEIZURE USING ANN

Artificial Neural Network has been used in a widely area as medicine, science or economy. Among the most important medical aspects are considered the good interpretation of data and setting the diagnosis. But medical decision making becomes a very hard activity because the human experts, who have to make decisions, can hardly process the huge amounts of data. So they need a tool that should be able to help them to make a good decision. They could use some expert systems or artificial neural networks, which are part of artificial intelligence (Albu and Ungureanu, 2005).

ANN has been successfully applied to various areas of medicine, such as diagnostic systems, biochemical analysis, image analysis, and drug development (Siganos, 1995). Most applications of neural networks to medicine are classification problems; that is the task is on the basis of the measured features to assign the patient (or biopsy or EEG or MRI) to one of a small set of classes (Ripley and Ripley, 1998).

Neural network has been proven of their capabilities in many domains such as medical application. Neural network with ability to learn by example makes them very flexible and powerful in medical diagnosis. Neural network show that experience from expertise is not enough in diagnosis. Nowadays, physicians combined this opportunity that give by neural network and their expertise to detect early stage of patient's disease (Salim, 2004).Artificial neural networks have a very important role in image analysis. ANNs are being used together with processing of digital image in recognition and classification. They are used in pattern recognition because of their capacity to learn and to store knowledge (Siganos, 1995; Salim, 2004).

In medicine diagnosis of an illness is as important as cure phase. A successful cure phase depends on successful diagnostic. Radiological scanning methods have great importance. Nowadays to diagnose, MR imaging methods are frequently used.

MR is also commonly preferred and used in radiology to visualize the structure and function of the body and also used in diagnosis of brain diseases.

This study aims assisting doctors on diagnosis process. To serve this purpose, ANN method which represents a solution, is used to diagnose tumor, meningitis and seizure from MR images.

Supervised learning and backpropagation is used in implementation for ANN model. Firstly MR images are transformed into inputs which can be used by network. Training data with desired outputs are supplied to the network. Then testing data is given to the network and outputs are observed. ANN is used as classifier to separate MR images into three group as tumor, meningitis and seizure.

MR images are used to diagnose tumor, meningitis and seizure. Sample MR images are collected from radiology department of Fatih University Hospital. Samples are collected from 30 patient for every pathology. 20 of them are used as input data to train ANN network, 10 of them are used for testing.

6.1 PREPROCESSING

MR images are RGB format. At RGB format each pixel has three values which represents red, green and blue color ratios. Each color has numerical value which is between 0 – 255. Firstly they are turned into gray level format. With using gray level format, data is reduced. AT RGB format pixel is represented by 3 values but at gray level format a pixel represented by only one value. Gray level images includes gray level colors between black and white. Each pixel has a numerical value which is between 0 – 255.

Dimensions of sample images are variable. Resizing are performed on MR images and new size of all samples are 240 x 240. All images are cut into 8x8=64 pieces. Each pieces dimension is 30x30. Subdivisions of MR image is shown at Figure 6.1.

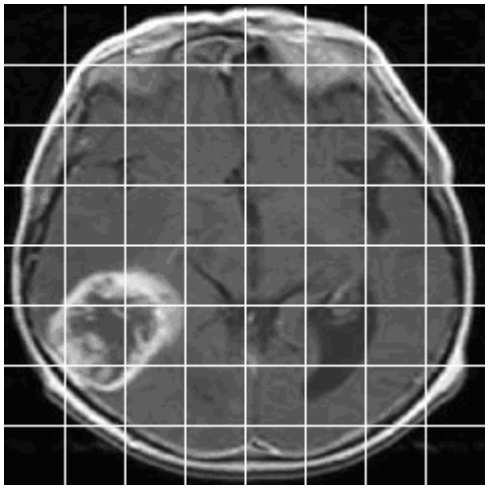


Figure 6.1 Subdivisions of MR image

6.1.1 Deblurring

Deblurring can be used effectively when no information about the distortion (blurring and noise) is known. The algorithm restores the image. To obtain clear images deblurring algorithm is used. MATLAB image processing toolbox is used for deblurring algorithm. But clear results are not observed, we understand that it is not so suitable to use in our study and debblurring process is not used for preprocessing. Deblurred images can be shown at Figure 6.2.

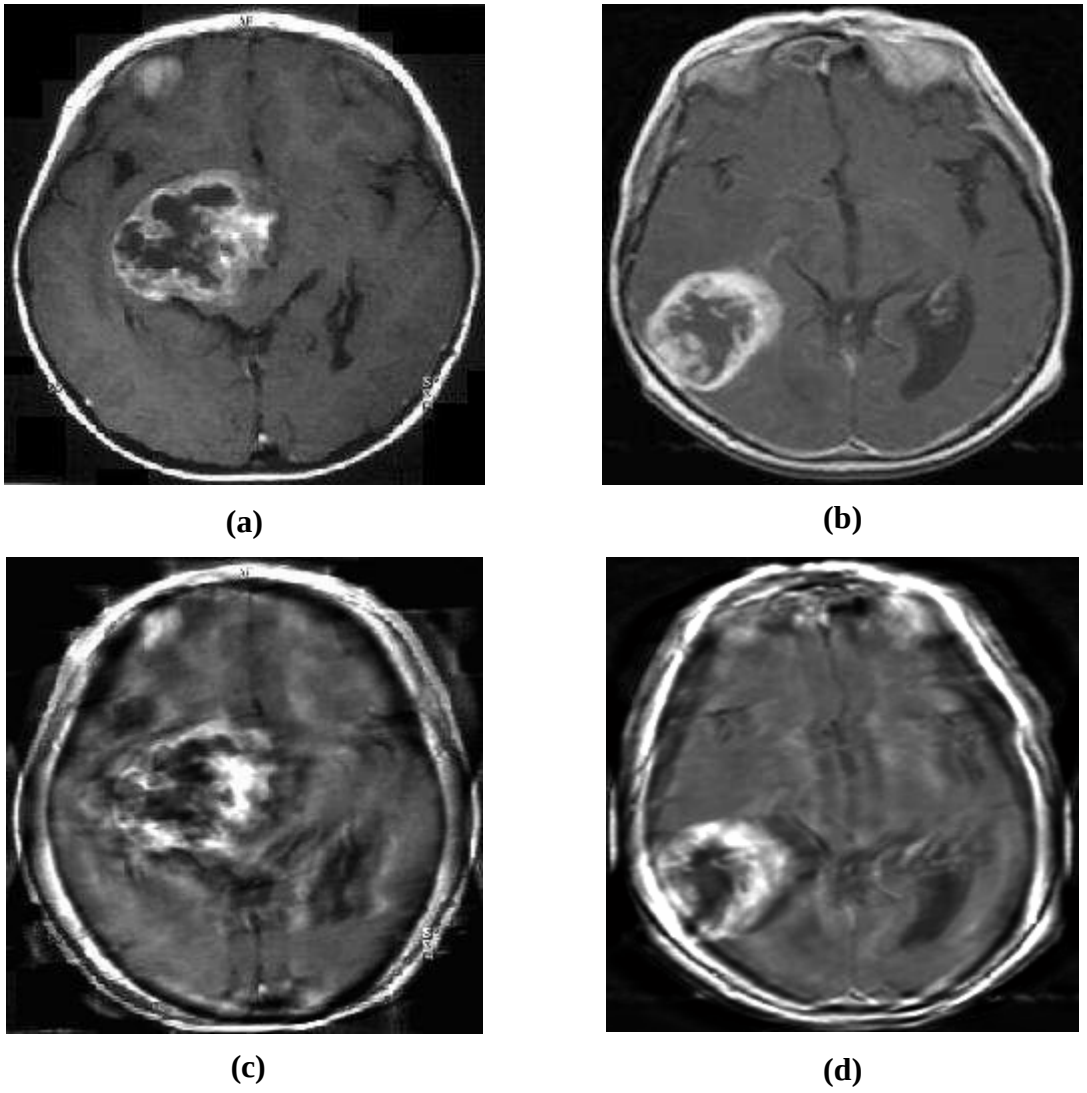


Figure 6.2 (a) (b) Tumor Images (c) (d) Deblurred Tumor Images

6.2 FEATURE EXTRACTION

Feature extraction in an important step for applications which need to cope with huge or redundant data. It is a special form of dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (much data, but not much information) then the input data will be transformed into a

reduced representation set of features which also named features vector. Transforming the input data into the set of features is called features extraction.

If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which overfits the training sample and generalizes poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy.

6.2.1 Arithmetic Mean

A mathematical representation of the typical value of a series of numbers, computed as the sum of all the numbers in the series divided by the count of all numbers in the series. Arithmetic mean is commonly referred to as "average" or simply as "mean" (Abramowitz and Stegun, 1972).

The arithmetic mean of a set of values is the quantity commonly called "the" mean or the average. Given a set of samples, the arithmetic mean is:

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} X_i \qquad (6.1)$$

In the equation, N is the number of pixels in the image, x_i is the value of pixel *i*.

Dimension of original image is 240x240 pixels. Images are divided into 8 equal smaller parts vertically and horizontally. 64 subdivisions are obtained. Each dimension of subdivision is 30x30 pixels. For each sub division arithmetic mean is calculated. The result

is divided by 100 to normalize the values between 0 and 1. Feature vector has 64 elements which represents arithmetic values of each sub dimensions.

Size of original image is 240x240. Size of sub division is 30x30 and size of feature vector is 64. MR images are divided into 64 equal part. Sub divisions are illustrated at Figure 6.3.

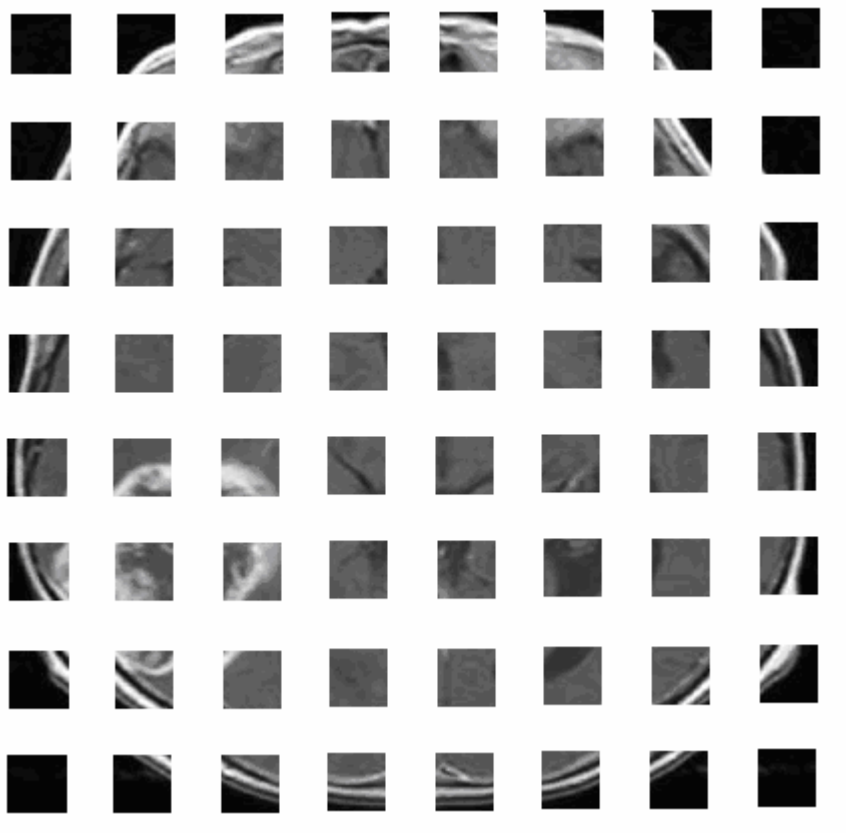
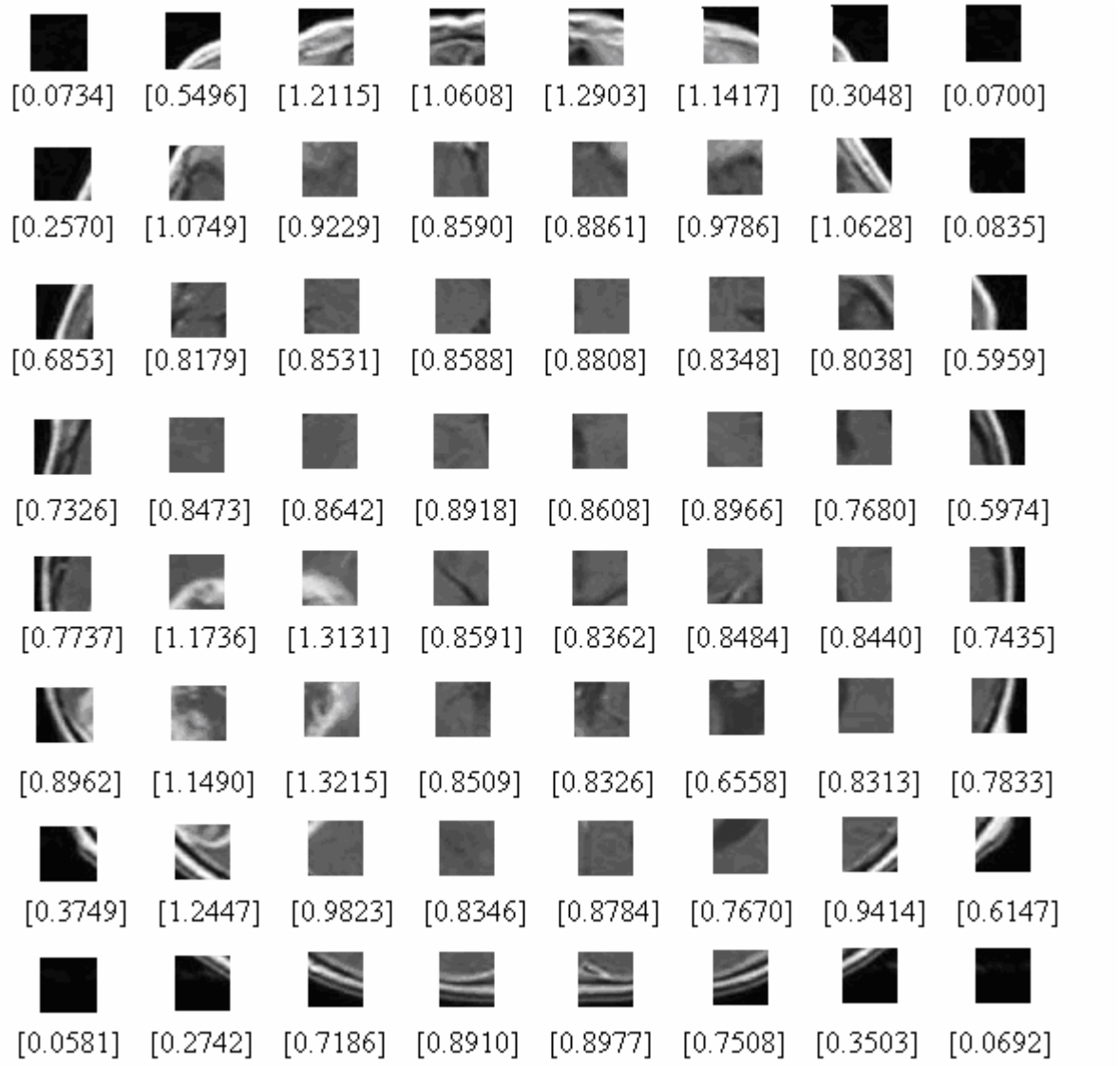


Figure 6.3 Expanded subdivisions of MR image

For each sub division, arithmetic mean is calculated then feature vector is obtained. It is shown at Figure 6.4.



Feature Vector =>[0.0734 0.5496 1.2115 …… 08 0.3503 0.0692]

Figure 6.4 Subdivisions to calculate arithmetic mean

6.2.2 Wavelet Transformation

Wavelet transformation is a tool which extracts different frequency components of data. The wavelet transformation of a signal evolving in time depends on two variables, frequency change scale and time. Wavelet provides a methodology for time-frequency localization (Ruskai et al. 1992, Hees-Nielsen and Wickerhauser 1996).

Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. Wavelet algorithms process data at different scales or resolutions. If we look at a signal with large "window," we would notice gross features. Similarly, if we look at a signal with a small "window," we would notice small discontinuities. The result in wavelet analysis is to "see the forest and the trees." (Amara, 2008) .

Wavelet transformations which is the representation of a function by wavelets, is widely used in various areas of data processing.

The fast Fourier transform (FFT) and the discrete wavelet transform (DWT) are both linear operations that generate a data structure that contains $\log_2 n$ segments of various lengths, usually filling and transforming it into a different data vector of length (Amara, 2008).

DWT analysis produces approximation coefficients matrix and details coefficients (horizontal, vertical, and diagonal) matrices by decomposition of the input matrix. The original matrix can be constructed from these vectors (Kul, 2008).

In the study, images are analyzed with DWT transformation tool in MATLAB. In DWT, the number of approximation coefficient is 120x120=14400. These coefficients are considered as the inputs to the ANN models and the size of the input vector. Wavelet transformation can be shown at Figure 6.5.

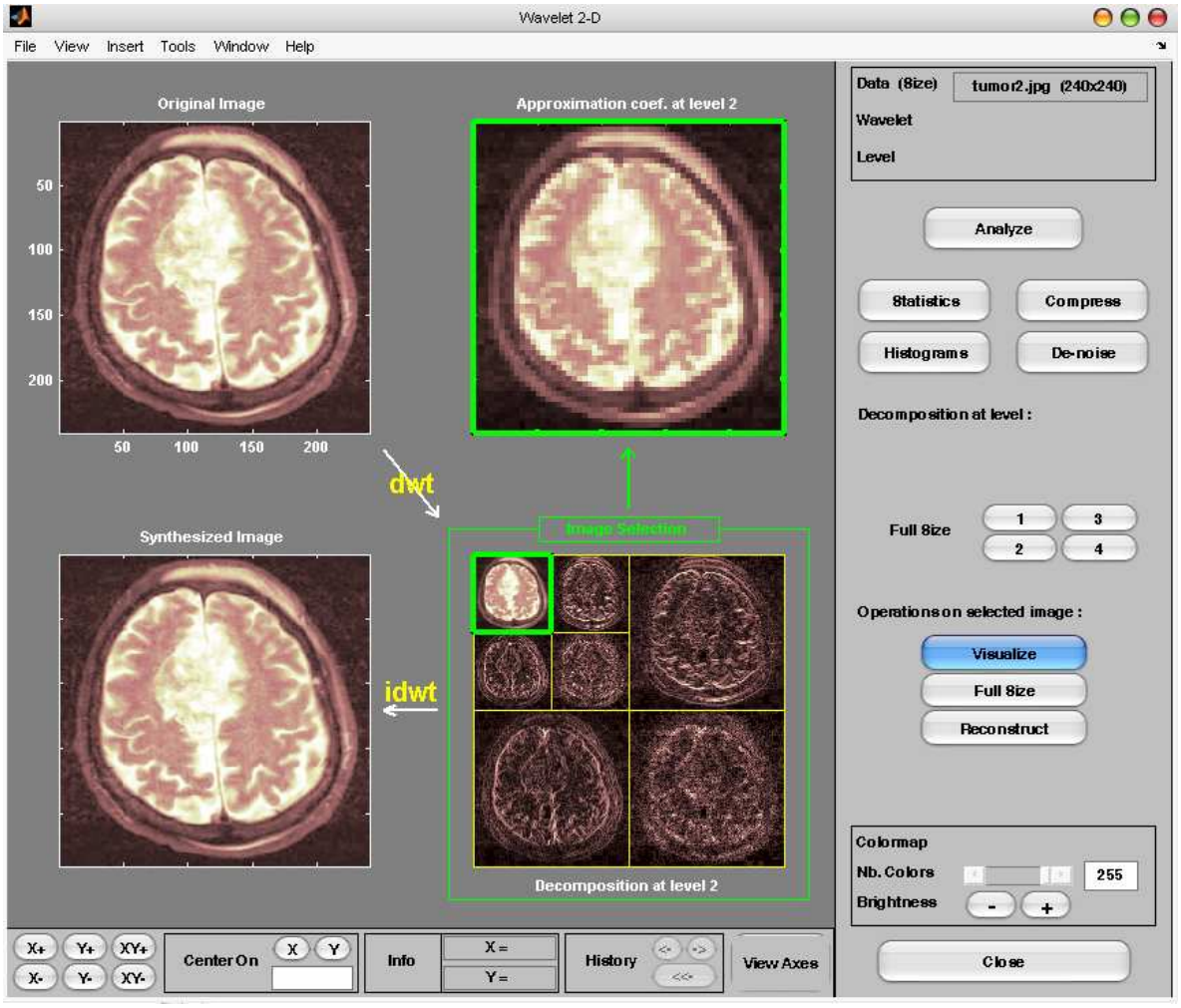


Figure 6.5 Graphical Interfaces for DWT (Matlab Output)

Wavelet approach is not used in the implementation because DWT methods cannot reduce the size of feature (input) vector to appropriate size.

6.3 IMPLEMENTATION

In this study; ANN is used to classify brain disease from MR images. Backpropogation and supervised learning algorithm is performed on ANN application. ANN has three layers which consist of one input, one output and one hidden layer.

The number of nodes in the input layer is defined by inputs. Images' pixels can be used as input vector but each image has 240x240= 57600 pixels which is too large and redundant to be processed. The input data is transformed into a reduced representation. To decrease input size, feature extraction which is a special form of dimensionality reduction, is used. By using feature extraction, the data which will be used as input vector, is obtained as a reduced representation which means a small subset of features. To obtain feature vector which has smaller dimension, images are divided into 8 equal smaller parts vertically and horizontally. 64 subdivisions are obtained (8x8=64) and for each subdivision arithmetic mean is calculated. Each arithmetic mean is normalized between 0 and 1 by dividing by 100. Feature vector which will be used as input vector and will be fed to input layer, is obtained. Feature vector has 64 elements which represent arithmetic mean of each subdivision and it means model has 64 nodes in the input layer.

The number of nodes in the hidden layer is generally decided by the greater number of nodes whether in the output or input layer. The number of nodes in input layer is greater than in the output layer and so the number of nodes in hidden layer is set to 64. Neural Network model which was used in the study has one input, one hidden and one output layer. Input layer has 64 nodes. Hidden layer has 64 nodes.

The number of nodes in the output layer is decided by the number of classes in the application. Main model has 4 classes which represents tumor, meningitis, seizure and normal. Output layer has 4 nodes which represent these classes. In the output layer, if first node is set to 1, others are set to 0, it means the output signal represents tumor. In the study three sub model is also used. First sub model outputs are tumor and normal. Second sub model outputs are meningitis and normal. Third sub model outputs are seizure and normal. Main model outputs are tumor, meningitis, seizure and normal.

A software program about ANN developed by Prof. Dr. Bekir KARLIK is used in the implementation. The program uses backpropagation algorithm as the learning algorithm. Sigmoid function is used as the activation function. There are 1 input layer, 1 hidden layer and 1 output layer in the model. There are 64 nodes in the input layer and learning rate is set to 0.95. The number of nodes in the hidden layer is set to 64.

In first sub NN model outputs are tumor and normal. Model has 3 layer; one input one output and one hidden layer. Input layer has 64 node like the main model. Hidden layer has 64 node and output layer has 2 nodes which represent tumor and normal. Illustration of the first sub NN model is shown in Figure 6.6.

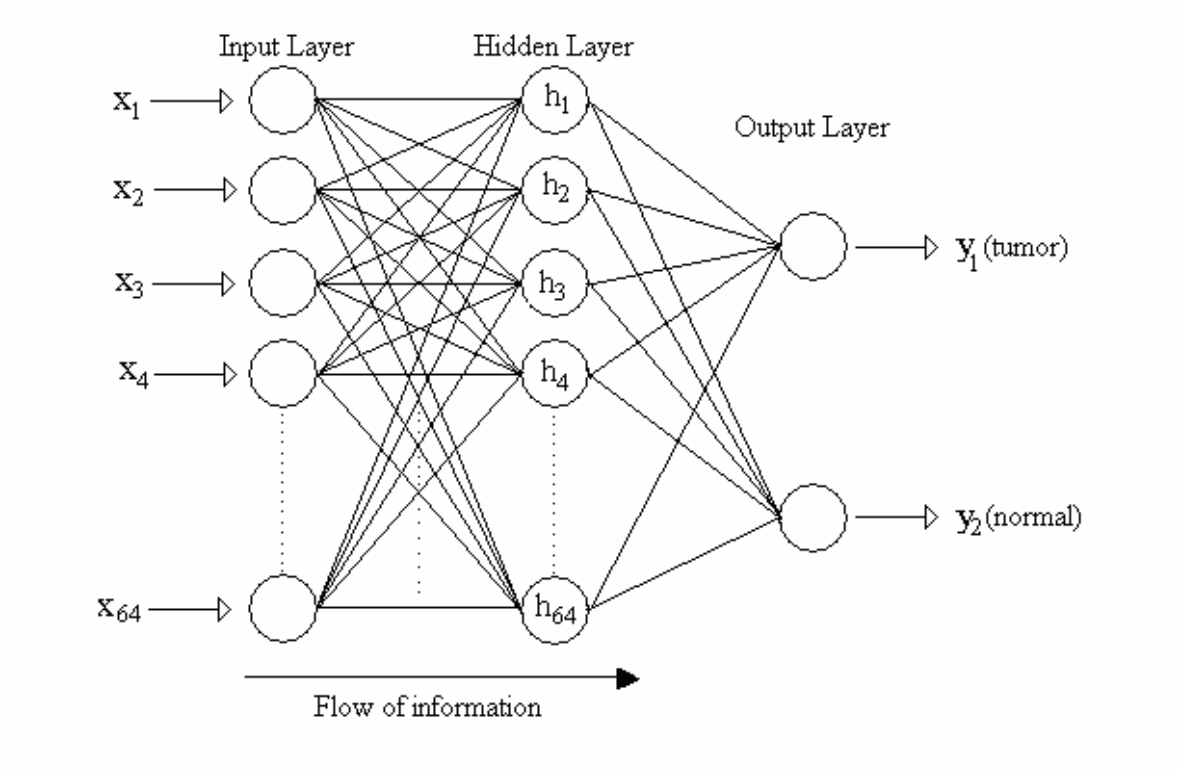


Figure 6.6 First Sub NN Model used in the study

At training phase, for tumor 20 sample sets, for normal 20 sample sets, totally 40 sample sets of input vector is used. input vectors is fed to the ANN with the 0.95 learning rate. Then for each disease 10 samples are used for testing.

Training set is applied to the network and iteration number is increased from 100 to 1000 iterations. Mean square error (MSE) is observed during training phase. Table 6.1 and Figure 6.7 show the relation between iteration number and error rate.

Table 6.1 Iteration number and error rate of first sub NN Model

Iteration	Error rate
100	0.1385288699
200	0.1025465220
300	0.0087531583
400	0.0081412226
500	0.0078127345
600	0.0075240373
700	0.0073289579
800	0.0071660931
900	0.0070155314
1000	0.0068712807

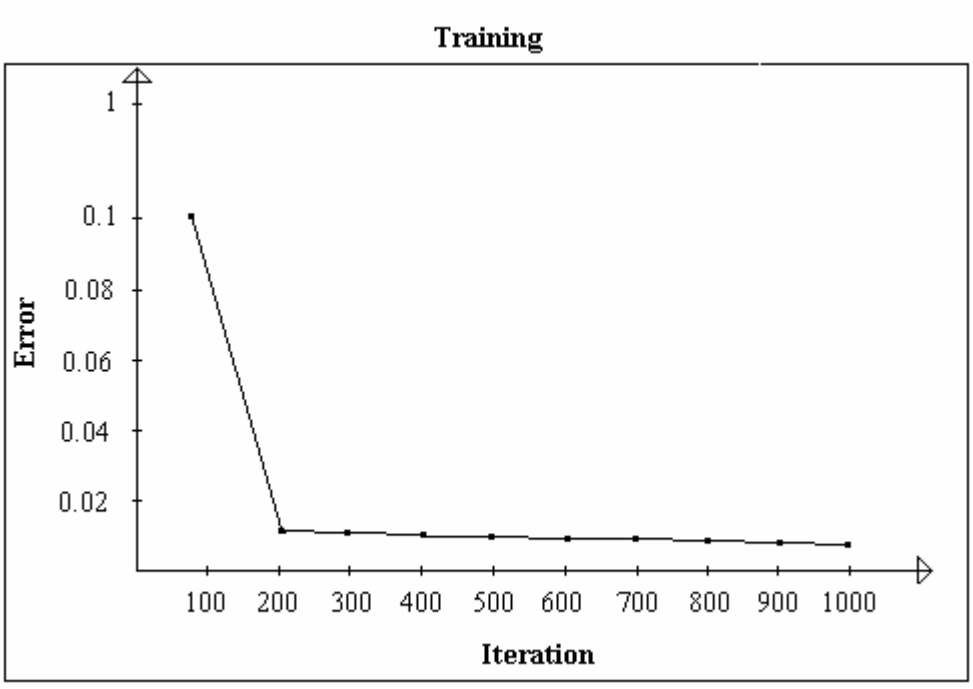


Figure 6.7 Training Graphic of first sub NN model

For testing 20 sample sets are used. Number of the correct and incorrect outputs can be shown at Table 6.2.

Table 6.2 Number of correct and incorrect outputs of first model(data used only testing)

Type of Disease	Number of Test Sample	Number of Correct Outputs	Number of Incorrect Outputs	Accuracy
Tumor	10	10	0	%100
Normal	10	10	0	%100
Total	**20**	**20**	**0**	**%100**

In the second sub NN model outputs are meningitis and normal. Model has 3 layer; one input one output and one hidden layer. Input layer has 64 node like the main model. Hidden layer has 64 node and output layer has 2 nodes which represent meningitis and normal. Illustration of the second sub NN model is shown in Figure 6.8.

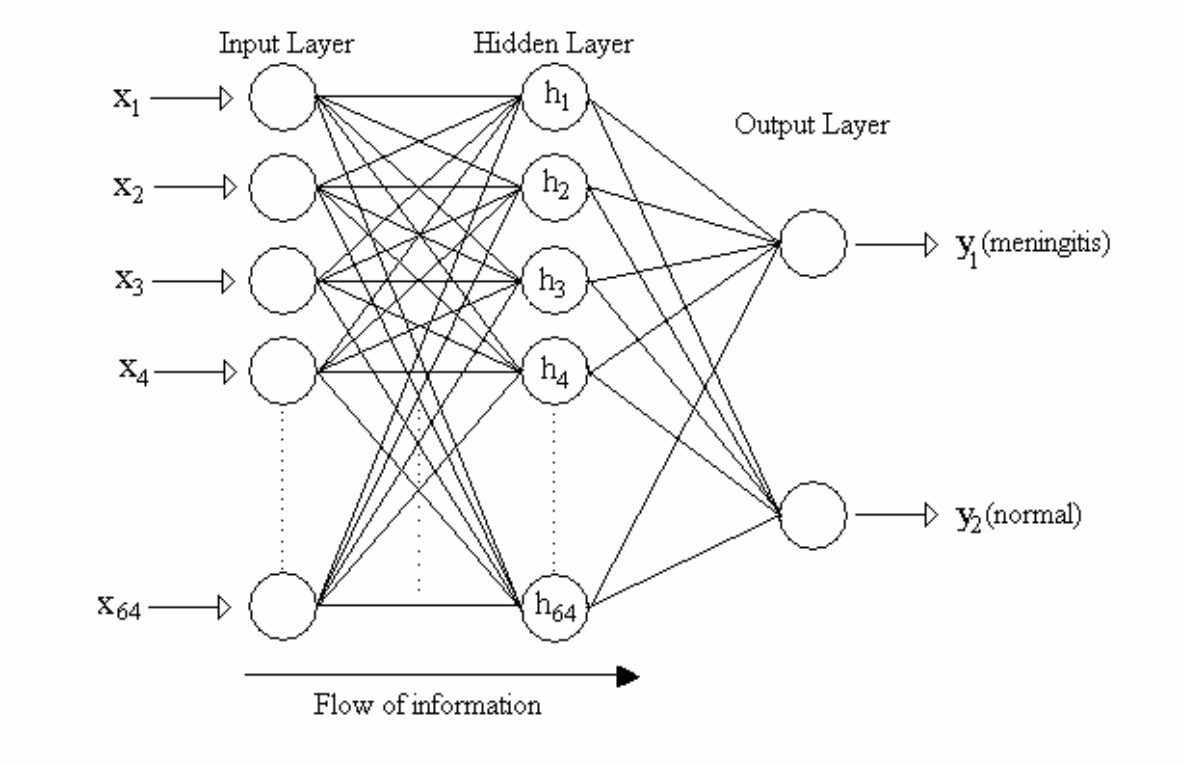


Figure 6.8 Second Sub NN Model is used in the study

At training phase, for meningitis 20 sample sets, for normal 20 sample sets, totally 40 sample sets of input vector is used. input vectors is fed to the ANN with the 0.95 learning rate. Then for each disease 10 samples are used for testing.

Training set is applied to the network and iteration number is increased from 100 to 1000 iterations. Mean square error (MSE) is observed during training phase. Table 6.3 and Figure 6.5 show the relation between iteration number and error rate.

Table 6.3 Iteration number and error rate of second sub NN model

Iteration	**Error rate**
100	0.2367582051
200	0.0126453887
300	0.0116117752
400	0.0113835300
500	0.0112537955
600	0.0111450532
700	0.0110353394
800	0.0109169901
900	0.0107879559
1000	0.0106491544

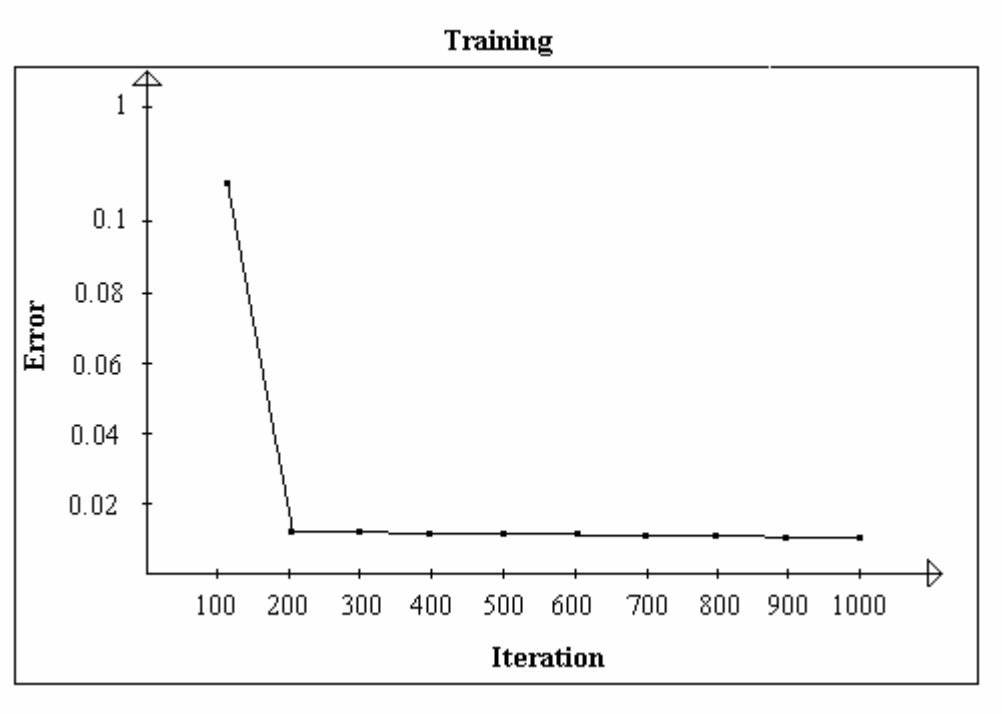


Figure 6.9 Training Graphic of second sub NN model

For testing 20 sample sets are used. Number of the correct and incorrect outputs can be shown at Table 6.4.

Table 6.4 Number of correct and incorrect outputs second model(data used only testing)

Type of Disease	Number of Test Sample	Number of Correct Outputs	Number of Incorrect Outputs	Accuracy
Meningitis	10	9	1(normal)	%90
Normal	10	10	0	%100
Total	**20**	**19**	**1**	**%95**

In the third sub NN model outputs are seizure and normal. Model has 3 layer; one input one output and one hidden layer. Input layer has 64 node like the main model. Hidden

layer has 64 node and output layer has 2 nodes which represent seizure and normal. Illustration of the third sub NN model is shown in Figure 6.10.

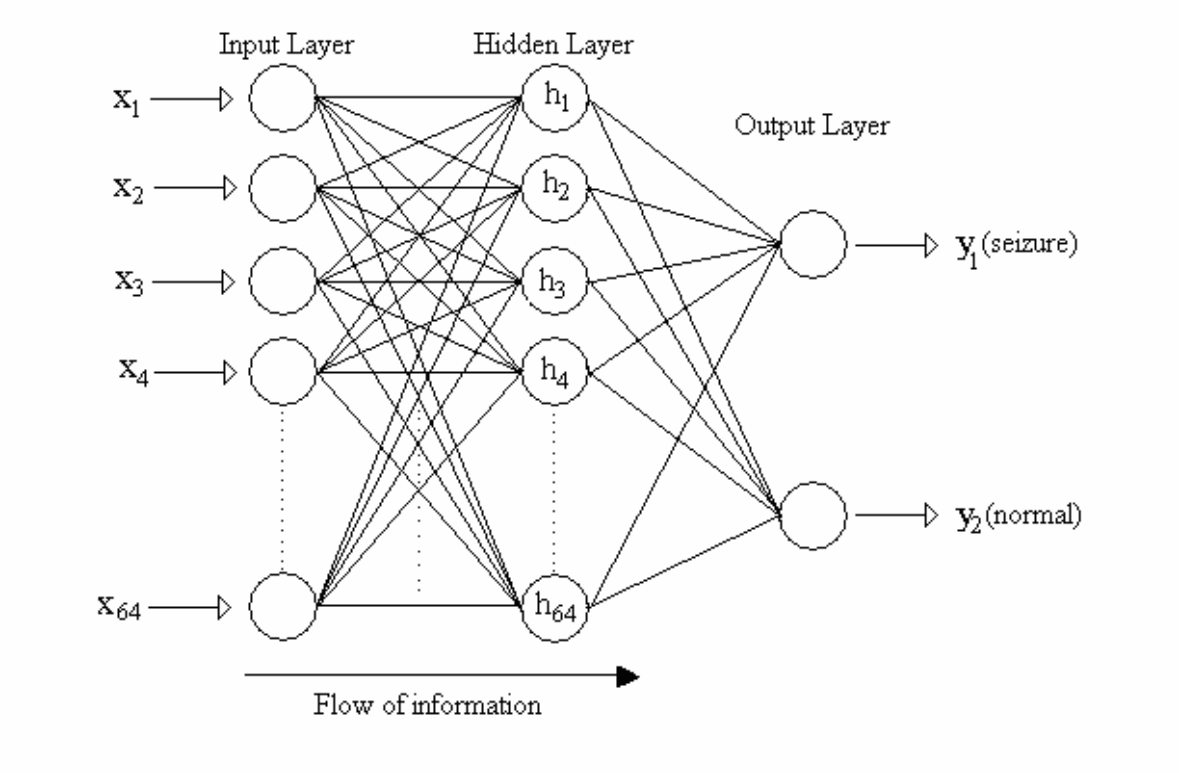


Figure 6.10 Third Sub NN Model is used in the study

At training phase, for seizure 20 sample sets, for normal 20 sample sets, totally 40 sample sets of input vector is used. input vectors is fed to the ANN with the 0.95 learning rate. Then for each disease 10 samples are used for testing.

Training set is applied to the network and iteration number is increased from 100 to 1000 iterations. Mean square error (MSE) is observed during training phase. Table 6.5 and Figure 6.11 show the relation between iteration number and error rate.

Table 6.5 Iteration number and error rate of third sub NN model

Iteration	Error rate
100	0.1030379676
200	0.0052778928
300	0.0042775933
400	0.0037930012
500	0.0034217012
600	0.0030884321
700	0.0037665056
800	0.0024481912
900	0.0021375823
1000	0.0018481603

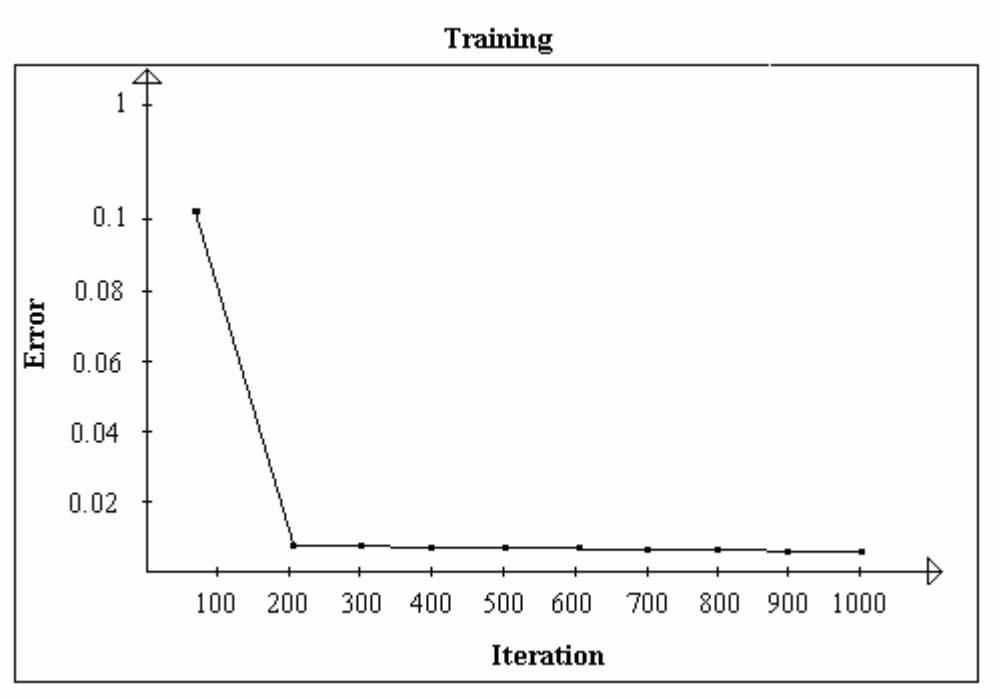


Figure 6.11 Training Graphic of third sub NN model

For testing 20 sample sets are used. Number of the correct and incorrect outputs can be shown at Table 6.6.

Table 6.6 Number of correct and incorrect outputs of third model(data used only testing)

Type of Disease	Number of Test Sample	Number of Correct Outputs	Number of Incorrect Outputs	Accuracy
Seizure	10	10	0	%100
Normal	10	10	0	%100
Total	**20**	**20**	**0**	**%100**

In the main NN model; outputs are tumor, meningitis, seizure and normal. Model has 3 layer; one input one output and one hidden layer. Input layer has 64 node like the main model. Hidden layer has 64 node and output layer has 4 nodes which represent tumor, meningitis, seizure and normal. Illustration of the first sub NN model is shown in Figure 6.4.

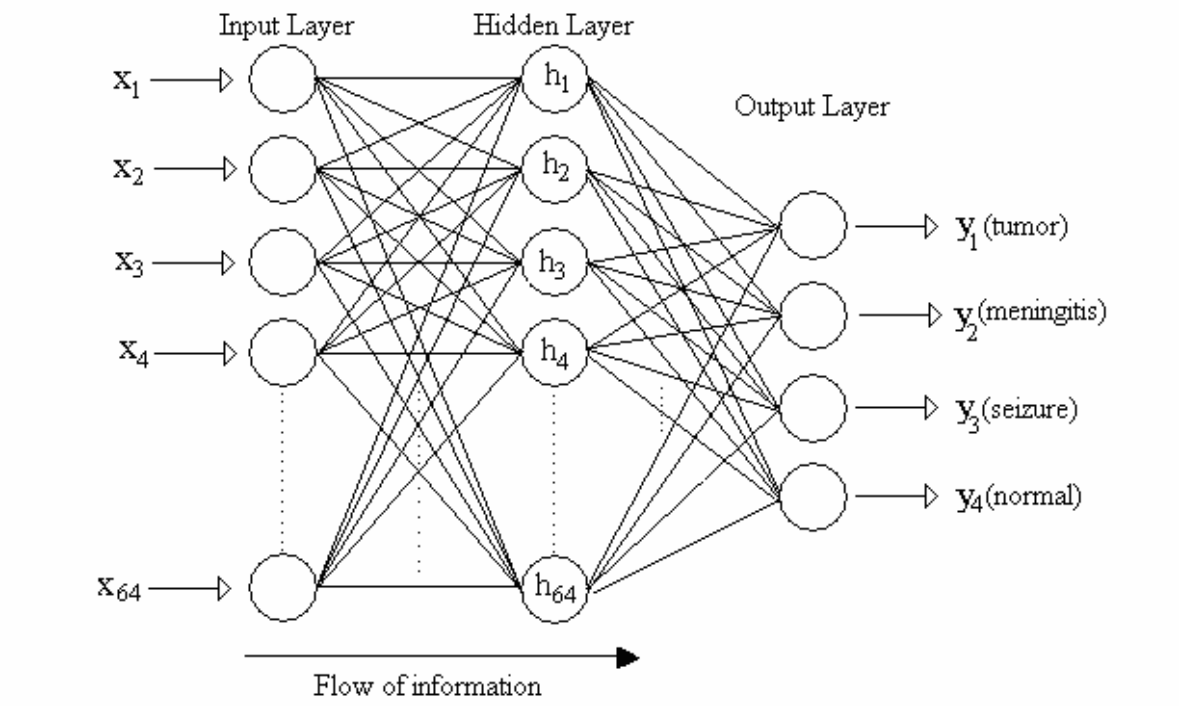


Figure 6.12 Main NN Model is used in the study

At training phase, for each brain disease 20 sample sets, for normal 20 sample sets, totally 80 sample sets of input vector is used. input vectors is fed to the ANN with the 0.95 learning rate. Then for each disease 10 samples are used for testing.

Training set is applied to the network and iteration number is increased from 100 to 1000 iterations. Mean square error (MSE) is observed during training phase. Table 6.7 and Figure 6.13 show the relation between iteration number and error rate.

Table 6.7 Iteration number and error rate

Iteration	**Error rate**
100	3.3789488846
200	0.7070283463
300	0.0217136670
400	0.0181522689
500	0.0165059393
600	0.0154039001
700	0.0143445099
800	0.0132267894
900	0.0122756836
1000	0.0115372273
1500	0.007436698
2000	0.005867965
2500	0.004857914

Training graphic is shown in Figure 6.13.

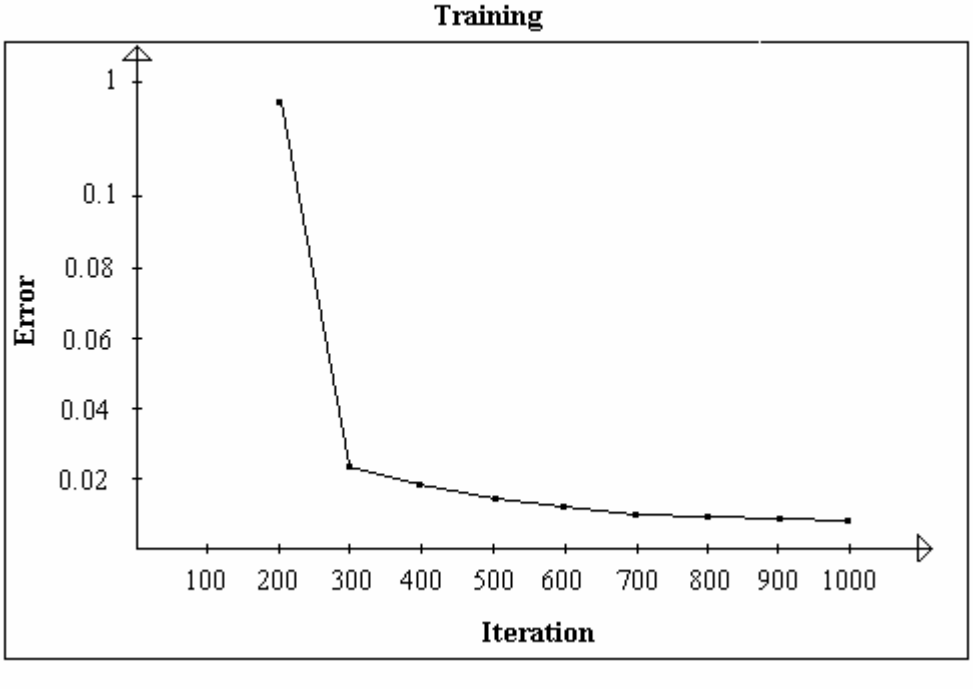


Figure 6.13 Training Graphic (Backpropogation)

For testing 40 sample sets are used. Number of the correct and incorrect outputs can be shown at Table 6.8 and Table 6.9.

Table 6.8 Number of correct and incorrect outputs(data used at training)

Type of Disease	Number of Test Sample	Number of Correct Outputs	Number of Incorrect Outputs	Accuracy
Meningitis	20	19	1(tumor)	%95
Seizure	20	19	1 (normal)	%95
Tumor	20	20	0	%100
Normal	20	20	0	%100
Total	**80**	**78**	**2**	**%97.5**

.

Table 6.9 Number of correct and incorrect outputs(data used only testing)

Type of Disease	Number of Test Sample	Number of Correct Outputs	Number of Incorrect Outputs	Accuracy
Meningitis	10	8	2(tumor, normal)	%80
Seizure	10	9	1 (normal)	%90
Tumor	10	9	1 (normal)	%90
Normal	10	10	0	%100
Total	**40**	**36**	**4**	**%90**

In this study Learning Vector Quantization (LVQ) and Elman is also used in the second and third implementation instead of feed-forward backpropogation. Performance of LVQ, backpropogation and Elman are compared. Only network model is changed. Layers and nodes are used as same as in the first implementation. MATLAB neural network toolbox is used for training and testing phases. Training graphic of LVQ which is obtained from MATLAB neural network toolbox is shown at Figure 6.14.

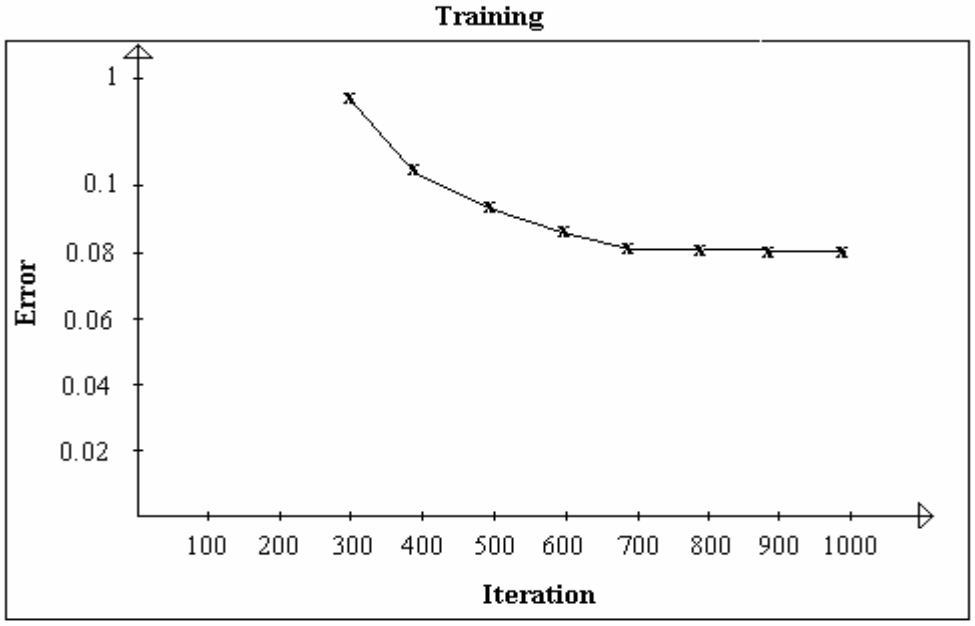


Figure 6.14 Training Graphic (LVQ)

Second implementation using LVQ is unsuccessful at training phase. Training is not obtained. Number of the correct and incorrect outputs can be shown at table 6.11.

Table 6.11 Number of correct and incorrect outputs of LVQ (data used only testing)

Type of Disease	Number of Test Sample	Number of Correct Outputs	Number of Incorrect Outputs	Accuracy
Meningitis	10	3	7(tumor)	%30
Seizure	10	5	5 (tumor)	%50
Tumor	10	10	0	%100
Normal	10	3	7(tumor)	%30
Total	**40**	**21**	**19**	**%55**

Training graphic of Elman which is obtained from MATLAB neural network toolbox is shown at figure 6.7.

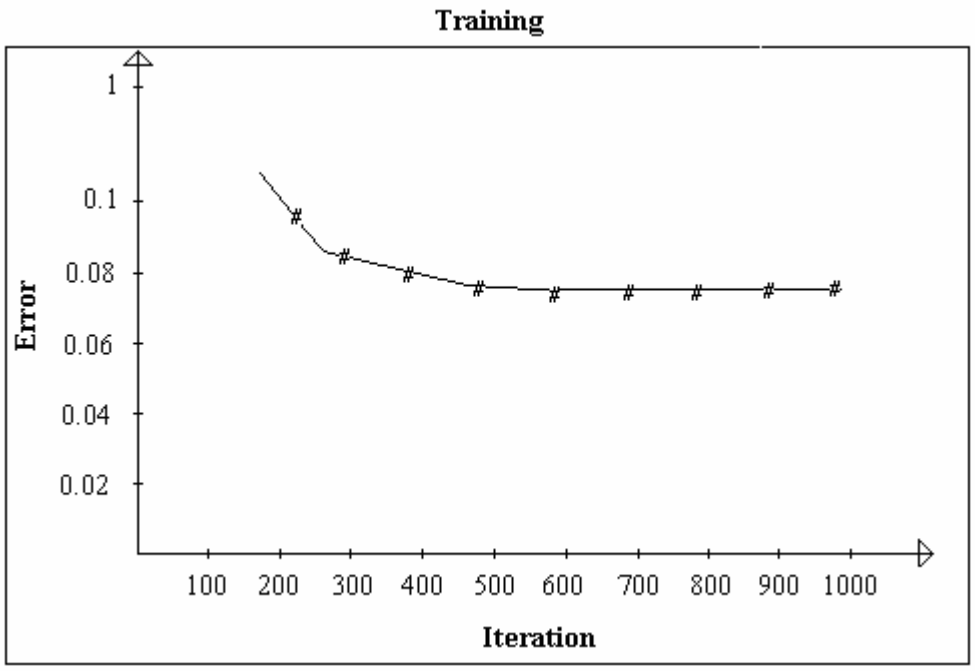


Figure 6.15 Training Graphic (Elman)

Third implementation using Elman is unsuccessful at training phase. Number of the correct and incorrect outputs of testing phase of Elman Network can be shown at table 6.11.

Table 6.11 Number of correct and incorrect outputs of Elman (data used only testing)

Type of Disease	Number of Test Sample	Number of Correct Outputs	Number of Incorrect Outputs	Accuracy
Meningitis	10	7	5 (2 Seizure, 1 Normal)	%70
Seizure	10	4	6 (4 tumor, 2 Normal)	%40
Tumor	10	8	2 (Normal)	%80
Normal	10	6	4 (2 tumor, 2 Seizure)	%60
Total	**40**	**25**	**15**	**%62,5**

Comparing of training graphics of Backpropogation, LVQ and Elman can be shown at Figure 6.15.

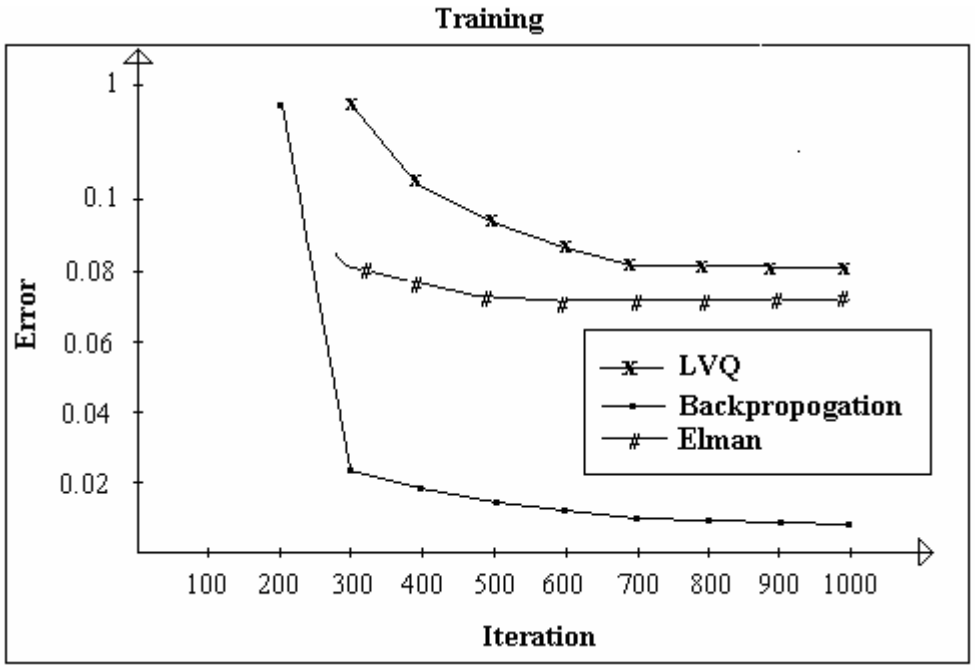


Figure 6.16 Training Graphics of Backpropogation, LVQ and Elman

Program screenshots are given in Appendix A.

CHAPTER 7

CONCLUSION

In this thesis, a system is designed which can help to diagnosis of brain diseases. This system is also able to be taught and to apply learned issues to the certain cases. MR images are used in diagnosis of brain diseases. Because of its ability to learn, Artificial Neural Network (ANN) is preferred in this system. The designed system has the ability to diagnose tumor, meningitis and seizure. The designed application has some distinct properties like the ability to learn, to be trained and to be adapted to new circumstances.

In the designed ANN system, supervised learning approach and backpropogation models are used. At the end, successful results are obtained and presented.

Supervised learning is a system which uses outcomes of some certain data samples to predict new and unknown ones.

MR images related brain diseases were collected from radiology department of Hospital of Fatih University. MR images are at JPEG format and have RGB color mode. At RGB format each pixel has three values which represents red, green and blue. MR images are turned into gray level format. Gray level images includes only gray level colors between black and white. Each pixel has a numerical value which is between 0 – 255.

Dimensions of sample images are changeable. Resizing are performed on MR images and new size of all samples are 240 x 240 pixels. Some images have needless data as patient name or time etc. These parts are removed from the images to prevent noisy and not to damage accuracy of application.

Next step is performing feature extraction methods on the images. Feature extraction is the nearly most critical step for the ANN applications. The data which one is necessary or which one is useless, is decided, the data can be turned into a new format which will be shorten (become smaller) or the data can be cleaned from redundant. If the features extracted are carefully chosen, features set will extract the relevant information from the input data. Reduced representation can be used instead of the full size input.

To reduce size of inputs, images are divided into eight equal parts at horizontal and vertical. New 64 subdivision whose sizes are 30x30 pixels, are obtained. To generate feature vector which will be used as input vector, arithmetic mean of each subdivision is calculated. So the original image can be represented with the new values. Matlab imaging tool is used to divide MR image and calculate average arithmetic mean of each subdivision. The results are normalized between 0 and 1. These values construct input vector size of 64 input nodes.

In this application, the ANN is trained by totally 80 sample data which includes 20 normal, 20 tumor, 20 meningitis and 20 seizure sample images.

The application results are tested by totally 40 MR images which contains 10 normal, 10 tumor, 10 meningitis and 10 seizure images. In this test 38 diseases are truly diagnosed.

Because of the application is designed as a learning system, the sample data is very important. The much more and the better sample data are provided, the higher learning capacity the ANN will have.

If there are some improper results, relearning of the system is provided by giving new and true results to the system. Thus, the system learns from improper results and deals with these errors in the next time.

Certain characteristics of the developed application are:

- The learning ability from sample data,
- Continuity of the learning ability,

- Although at the present time the system is used only for diagnosis of tumor, meningitis and seizure, it is able to learn other diseases by sample data.

The application must not be used out of a specialist's control. This application is not an intelligent system for diagnosis. The system only helps doctors to diagnose some certain diseases.

In this application, some brain MR images are used. As the next level, new brain diseases can be added to the scope of the application.

REFERENCES

Abramowitz, M. and Stegun, I.A., *Handbook of Mathematical Functions with Formulas, Graphs, and Mathematical Tables 9th printing*, Dover, New York, 1972.

Acr Org, 2008. *http://www.acr.org/SecondaryMainMenuCategories/quality_safety/MRSafety/safe_mr07.aspx. page 2*, 2008.

Albu A., Ungureanu, L., "Artificial Neural Network in Medicine", *2nd Romanian-Hungarian Joint Symposium on Applied Computational Intelligence*, Budapest Tech - Hungary , Polytechnic University of Timisoara, Romania, Paper Id.7, 2005.

Aleksander, I.. and Msc. Morton, H., *An Introduction to Neural Computing*, Chapman and Hall, 1989.

Amara Graps, An Introduction to Wavelets, 2008. http://www.amara.com/ftpstuff/IEEEwavelet.pdf

Angus-Leppan, H., Parsons L.M., "Epilepsy: epidemiology, classification and natural history", *Medicine*, Vol.36, Issue 1, November 2008, pp. 573, 2008.

Arbib, A.M.(editor), *The Handbook of Brain Theory and Neural Networks 2nd ed*, The Mit Pres, London, 2002.

Ari, S., Saha, G., "In search of an optimization technique for Artificial Neural Network to classify abnormal heart sounds", *Applied Soft Computing"*, Vol. 9, pp. 330-340, 2008.

Aslantaş, V. and Kurban, R., *Yapay Sinir Ağları ve Coğrafi Bilgi Sistemlerindeki Uygulamaları*, TMMOB Harita ve Kadastro Mühendisleri Odası Ulusal Coğrafi Bilgi Sistemleri Kongresi, Karadeniz Technical University, Trabzon, 2007.

Bullinaria, J.A., "Learning Vector Quantization (LVQ) Introduction to Neural Computation : Guest Lecture 2", 2007. http://www.cs.bham.ac.uk/~pxt/NC/lvq_jb.pdf

CSE (School of Computer Science and Engineering), Recurrent Neural Networks, 2008. http://www.cse.unsw.edu.au/~waleed/phd/html/node37.html

Çavdaroğlu, G.Ç., *Manyetik Rezonans (MR) Görüntülerinin Üç Boyutlu Modellenmesi ve Analizi*, Yıldız Technical University, M.S. Thesis, 2006.

Das, R., Turkoglu, I., Sengur, A., "Diagnosis of valvular heart disease through neural networks ensembles", *Computer Methods and Programs in Medicine*, 2008

Deco, G. and Obradovic, D., *An Information-Theoretic Approach to Neural Computing*, Springer-Verlag, New York, 1996.

Dennis, S., Introduction to Neural Networks, 1997.
http://www.itee.uq.edu.au/~cogs2010/cmc/chapters/Introduction/

Di Luca, M., "Artificial neural networks allow the use of simultaneous measurements of Alzheimer Disease markers for early detection of the disease", *Journal of translational Medicine*, Vol. 3, pp. 30, 2005.

Efe, M.Ö. and Kaynak, O., *Yapay Sinir Ağları ve Uygulamaları*, Boğaziçi University, 2000.

Efe, M.Ö. and O. Kaynak, *Artificial Neural Networks and Their Applications*, Boğaziçi University Publications, 2004.

Elmas, Ç.,*Yapay sinir Ağları*,Seçkin Yayıncılık, 2003.

Gorban, Alexander N. and Rossiyev, Dmitrii A. and Dorrer, Mikhail G. "*MultiNeuron - Neural Networks Simulator for Medical, Physiological, and Psychological Applications"*, 1996. http://cogprints.org/3940/

Gösel, B.K., Karataş, M., Tan, M., Yıldırım, T., Kızılkılıç, O., Benli, S. and Yerdelen, D., "Late Onset Poststroke Seizures", *Journal of Neurological Sciences (Turkish*, Vol. 22, No. 4, pp. 388-393, 2005.

Güven, A., *Artificial Neural Networks Based Diagnosis of Some of The Eye Diseases by Using Ocular Electrophysiological Signals*, Ph.D. Thesis, Erciyes University, 2005.

Haacke, E. M., Brown, R. F., Thompson, M., Venkatesan, R., *Magnetic resonance imaging: physical principles and sequence design*, J. Wiley & Sons. ISBN 0-471-35128-8., New York, 1999.

Hagan, M., Demuth, H. and Beale, M., *Neural Network Design*, PWS Publishing Company, 1995.

Haykin, S., *Neural Networks: A Comprehensive Foundation 2nd ed*, Prentice Hall, New Jersey, 1998.

Haykin, S., "*Neural Networks: A Comprehensive Foundation*, Prentice Hall, New Jersey, 1999.

Hebb, D.O., *The Organization of Behaviour: A Neurophsychological Theory*, Wiley, New York, 1949.

Hopfield, J.J., "Neural networks and physical systems with emergent collectivecomputational abilities", *Proceedings of the National Academy of Sciences of the USA*, Vol. 79 no. 8 pp. 2554-2558, April 1982.

Kanal E, Barkovich AJ, Bell C, et al *(2007). "ACR Guidance Document for Safe MR Practices: 2007".* AJR Am J Roentgenol. ***188****: 1–27. doi:10.2214/AJR.06.1616. PMID 17515363.*, 2007.

Kanra, G., Ceyhan M. and Kara, A., "Menenjit I: etiyopatogenez", *Çocuk Sağlığı ve Hastalıkları Dergisi*, Vol. 46, pp. 57-66, 2003.

Karlık, B., *Artificial Neural Network Lecture Notes*, 2007.

Karlık, B., Şahin, Y.G., Ercan, T., Tavlı, T., *Bundle Branch Blocks Diagnosis using Neural Networks for Telecardiology*, 2006.
http://www.telemed.org.ua/UJTMMT/N1_06/article6.html

Kendall, G., Introduction to Artificial Intelligence (Course), 2008.
http://www.cs.nott.ac.uk/~gxk/courses/g5aiai/006neuralnetworks/neural-networks.htm

Kiyan, T., and Yildirim, T. "Breast Cancer Diagnosis Using Statistical Neural Networks", *International XII. Turkish Symposium on Artificial Intelligence and Neural Networks*, University Besiktas, Istanbul, Turkey, 2003.

Kiyan, T., Yıldırım, T., "Diagnostic performance of GRNN and RBFN on the breast cancer data", *Istanbul University - Journal of Electrical & Electronics Engineering*, Vol.4, No. 2, pp. 1149-1153, July 2004.

Koca, H.K., *Kontrast Tutucu Maddeli Meme MR'ı Örneğinde Yapay Sinir Ağları ile Görüntü Segmentasyonu*, Yıldız Technical University, M.S. Thesis, 2007.

Kohonen, T., "Self-organization of very large document collections: State of the art", *Proceedings of the 8th International Conference on Artificial Neural Networks*, Vol.1, pp. 65-74, Skovde, Sweden, 1998.

Kohonen, T., "Self-Organizing Maps", New York, 2001.

Kul, S., *Diagnosis of Lumbar Disc Hernia From Images Using Artificial Neural Network*, M.S. Thesis, Fatih University, 2008.

Ljunggren, S., "A simple graphical representation of fourier-based imaging methods". *J Magn Reson* **54** (2): 338–43. doi:10.1016/0022-2364(83)90060-4, September 1983.

Lisboa, P.J.G., "A review of evidence of health benefit from artificial neural networks in medical intervention" , *Neural Networks*, Vol. 15, pp.11-39, 2002.
http://www.cms.livjm.ac.uk/research/snc/pdf/Med%20Review%202002.pdf

Luhdorf, K., Jensen, L.K. and Plesner, A.M., "Etiology of seizures in the elderly", *Epilepsia*, pp. 458–463, 1986.

Mahamad, A.K., Saon, S., Abd Wahab M.H., Yahya, M.N. and M.I Ghazali, M.I., "Using Artificial Neural Network to Monitor and Predict Induction Motor Bearing(IMB) Failure", *International Journal of Engineering and Technology*, Vol. 4, No. 2, pp.134-140, 2007.

Master, T., *Practical Neural Network Recipes in C*, Morgan Kaufmann Publishers, San Francisco, California, 1993.

McCullagh, P. and Nelder, J.A., *Generalized Linear Models, 2nd ed.*, Chapman & Hall, London, 1989.

McCullloch, W.S. and Pitts, "A Logical calculus of the ideas immanent in nervous activity", *Bulletin of Mathematical Biophysics*, Vol. 5, pp.115-133, 1943.

Özbay, Y., Karlık B., "A Recognition of ECG Arrhythmia Using Artificial Neural Network", *23rd Annual International Conference IEEE Engineering in Medicine and Biology Society*, Istanbul-Turkey, 2001.

Öztemel E., *Yapay Sinir Ağları*, Papatya Yayıncılık, İstanbul, 2003.

Price, DL., de Wilde, JP., Papadaki, AM., Curran, JS., Kitney, RI., "Investigation of acoustic noise on 15 MRI scanners from 0.2 T to 3 T.". *Journal of Magnetic Resonance Imaging* **13** (2): 288–293. doi:10.1002/1522-2586(200102)13:2<288:: AID-JMRI1041>3.0.CO;2-P, Jan 2001.

Ripley, B. D. and Ripley, R. M. *Neural networks as statistical methods in survival analysis*, 1998. http://www.stats.ox.ac.uk/pub/bdr/NNSM.pdf

Ripley, B.D., *Pattern Recognition and Neural Networks*, Cambridge University Press, Cambridge, 1996.

Rosenblatt, F., "The perceptron: A probabilistic model for information storage and organization in the brain", *Psychological Review*, Vol. 65, pp. 386-408, 1958.

Rowland, L.P., *Merritt's Textbook of Neurology Ninth Edition*, Williams & Wilkins, Philadelphia, 1995.

Rumelhart, D.E., Hinton, G.E. and Williams, R.J., "Learning Representations by Backpropagation Errors", *Parallel Distributed Processing: Explorations in the Microstructure of Cognition* Vol. 1, pp. 318-362, 1986.

D. E. Rumelhart, D.E. and McClelland, J. L., "Parallel Distributed Processing: Explorations in the microstructure of Cognition", Vol. 1, MIT Press/Bradford Books, 1986.

Donald G. McNeil Jr, "M.R.I.'s Strong Magnets Cited in Accidents ", *The New York Times*, August 19, 2005.

Salim, N., *Medical Diagnosis Using Neural Networks*, 2004. http://www.generation5.org/content/2004/MedicalDiagnosis.asp

Sağıroğlu, S., Beşdok, E. and Erler, M., *Mühendislikte Yapay Zeka Uygulamaları*, Ufuk Kitabevi, Kayseri, 2003.

Sameen, A.K. "Back Propagation Neural Network for Medical Prognosis: A Comparison of Different Training Algorithms", *Electronic Journal of the School of Advanced Technologies*, Vol. 3 No.1, Idcode. 1138, 2001. http://myais.fsktm.um.edu.my/1138/

Siganos, D., *Neural Networks in Medicine*, 1995. http://www.doc.ic.ac.uk/~nd/surprise_96/journal/vol2/ds12/article2.html

Schiffmann, W., Joost, M. And Werner, R., Optimization of the Backpropagation algorithm for Training Multilayer Perceptrons, University of Koblenz,1994. http://www.cs.bham.ac.uk/~pxt/NC/schiffmann.bp.pdf

Stanford CSE, Feed-Forward Networks, 2008. http://cse.stanford.edu/class/sophomore-college/projects-00/neural-networks/Architecture/feedforward.html

Stamford CT US, Stamford Hospital price quotation, October 2008.

Stergiou, C. and D. Siganos, *Neural Networks*, 1996. http://www.doc.ic.ac.uk/~nd/surprise_96/journal/vol4/cs11/report.html

Temurtas, H., Yumusak, N., Temurtas, F., "A comparative study on diabetes disease diagnosis using neural networks", *Expert Systems with Applications"*, 2008.

The Open University, *Understanding Cardiovascular Diseases*, course book for the lesson *SK121 Understanding cardiovascular diseases*, printed by University Press, Cambridge, ISBN 9780749226770, pages 220 and 224, 2007.

Twieg, D., "The k-trajectory formulation of the NMR imaging process with applications in analysis and synthesis of imaging methods". *Med Phys* **10** (5): 610–21. doi:10.1118/1.595331, 1983.

Weissleder, .R., Elizondo, G., Wittenberg, J., Rabito, CA., Bengele, HH., Josephson, L., "Ultrasmall superparamagnetic iron oxide: characterization of a new class of contrast agents for MR imaging". *Radiology* **175** (2): 489–93. PMID 2326474. http://radiology.rsnajnls.org/cgi/pmidlookup?view=long&pmid=2326474,May 1990.

Widder, DJ., Greif, WL., Widder, KJ., Edelman, RR., Brady TJ., "Magnetite albumin microspheres: a new MR contrast material". *AJR Am J Roentgenol* **148** (2): 399–404. PMID 3492120, 01 February 1987.
http://www.ajronline.org/cgi/pmidlookup?view=long&pmid=3492120.

Wikibooks, Artificial Neural Networks/Competitive Models, 2008.
http://en.wikibooks.org/wiki/Artificial_Neural_Networks/Competitive_Models

Willamette, Simple Competitive Learning , 2008.
http://www.willamette.edu/~gorr/classes/cs449/Unsupervised/competitive.html

Yurtoğlu, H., "Yapay Sinir Ağları Metodolojisi ile Öngörü Modellemesi: Bazı Makroekonomik Değişkenler için Türkiye Örneği", Expertness Thesis, State Planning Organization., 1989.

Zhang, N., "*Advanced Fault Diagnosis Techniques and Their Role in Preventing Cascading Blackouts*", Ph.D. Thesis, Texas A&M University, 2006.

APPENDIX A

SOFTWARE

In this study, MATLAB by Mathworks company and program coded by Bekir KARLIK are used in the implementation.

MATLAB is a software tool, used in engineering and scientific applications requiring mass amount of numerical calculations, image processing and advanced level programming.

MATLAB is used for image processing, calculating mean of sub dimensions to obtain feature vector which means input vector.

MATLAB CODES

Image transforming from RGB format to gray level format

```
I = imread('tumor1.jpg');
J = rgb2gray(I);
figure, imshow(I), figure, imshow(J);
imwrite(J, 'tumor1.jpg')
```

Image resizing

```
I = imread('tumor1.jpg');
B = imresize(I,[240 240], 'nearest');
figure, imshow(B);
imwrite(B, 'tumor1.jpg');
```

Deblurring

```
I1 = imread('tumor1.jpg');
I2 = deconvlucy(I1,PSF,5);
```

Aritmetic mean

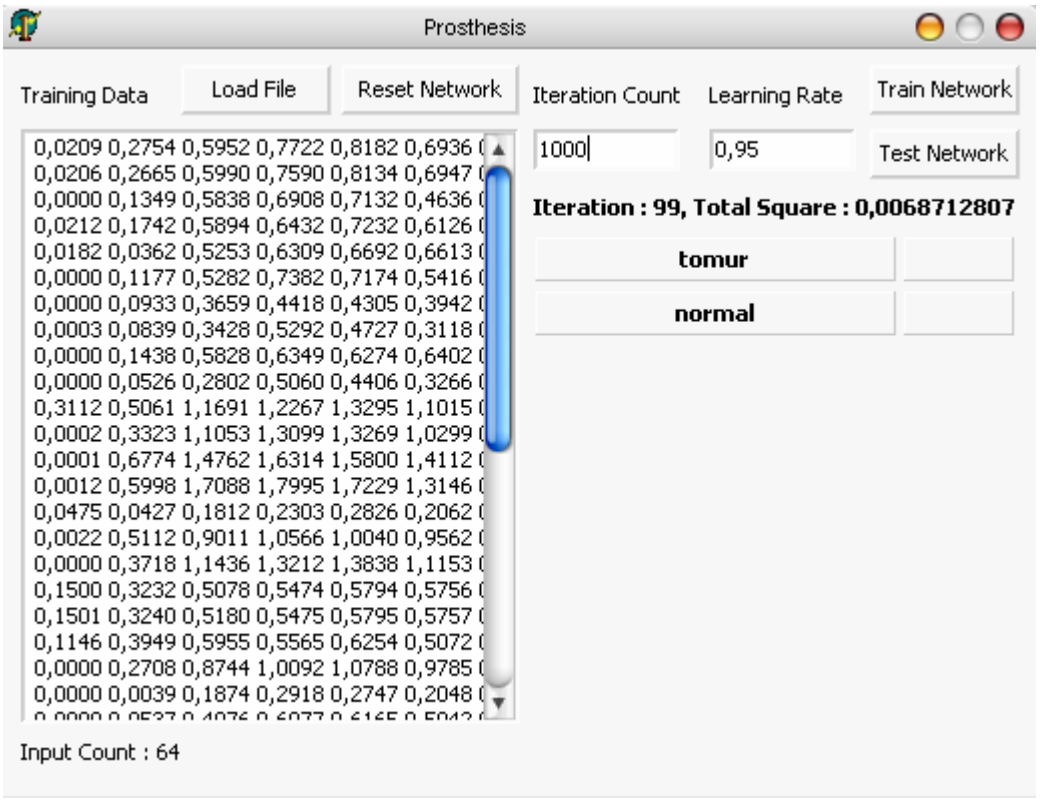
```
clear
t = intmax('uint64');
t =0;
R=imread('tumor1.jpg');
I=double(R);
for i = 1:8
for j = 1:8
for k = (((i-1)*30)+1):(i*30)
for l = (((j-1)*30)+1):(j*30)
          t=t + I(k,l);
end
end
S(i,j)=t/(900);
S(i,j)=S(i,j)/100;
t = 0;
end
end;
```

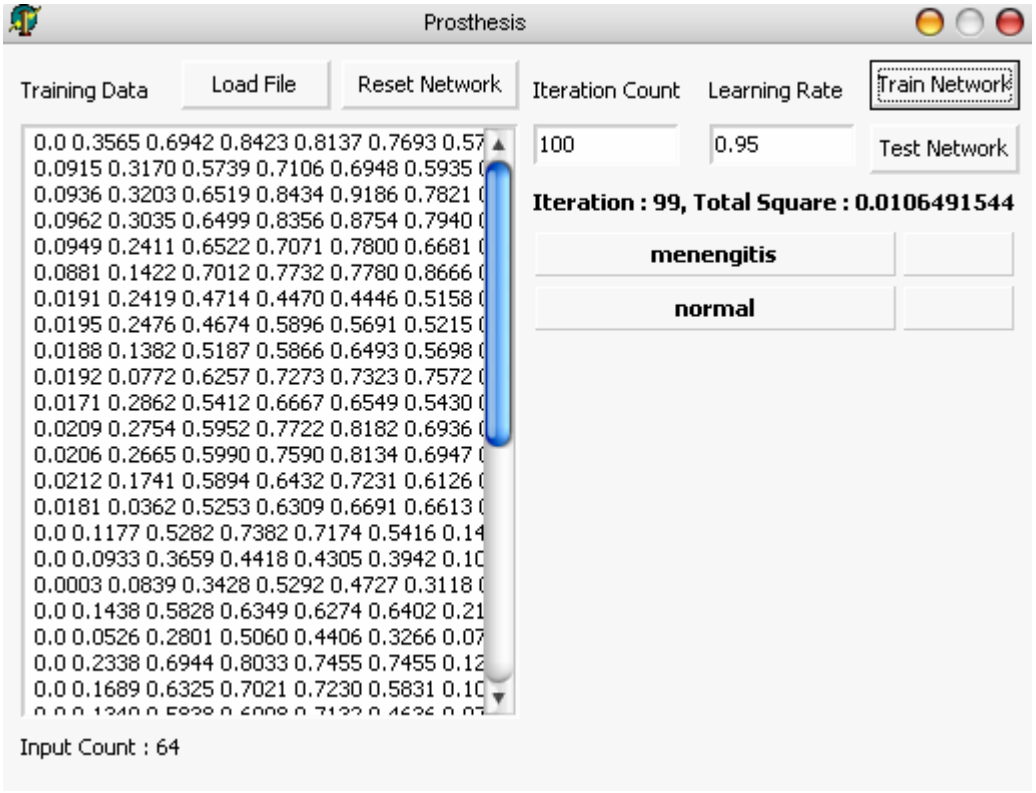
ANN PROGRAM

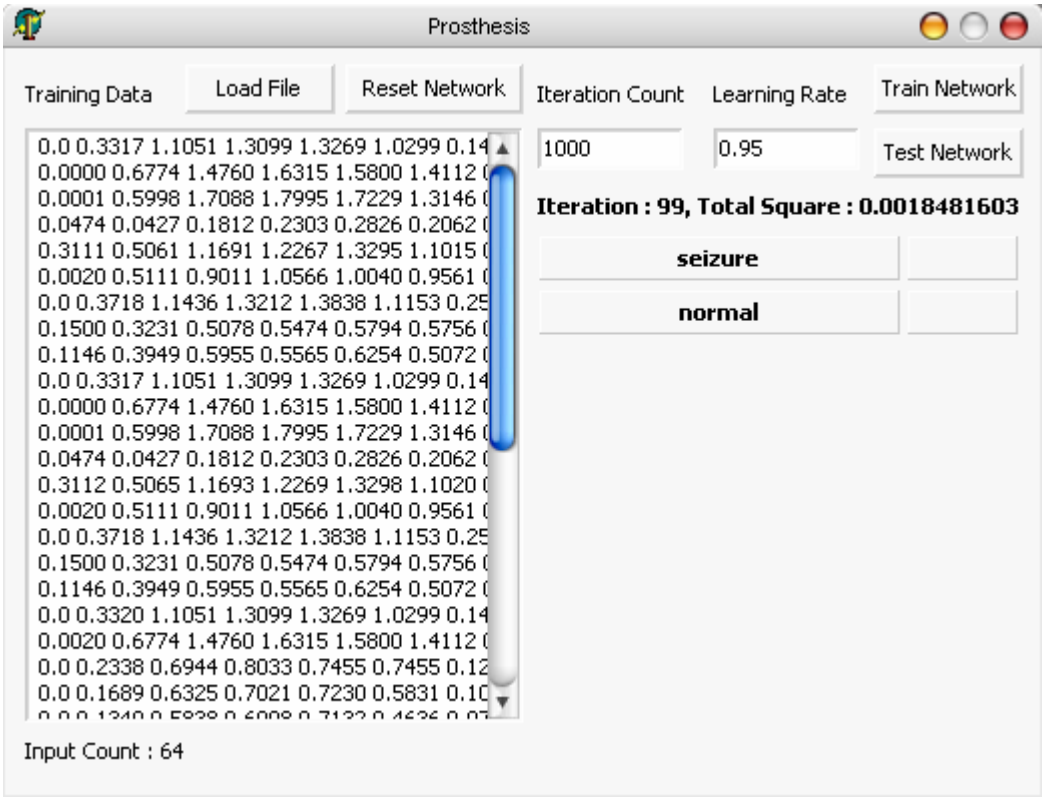
Classifications of brain disease are presented in the study. In the first classification, outputs are tumor, meningitis and seizure.

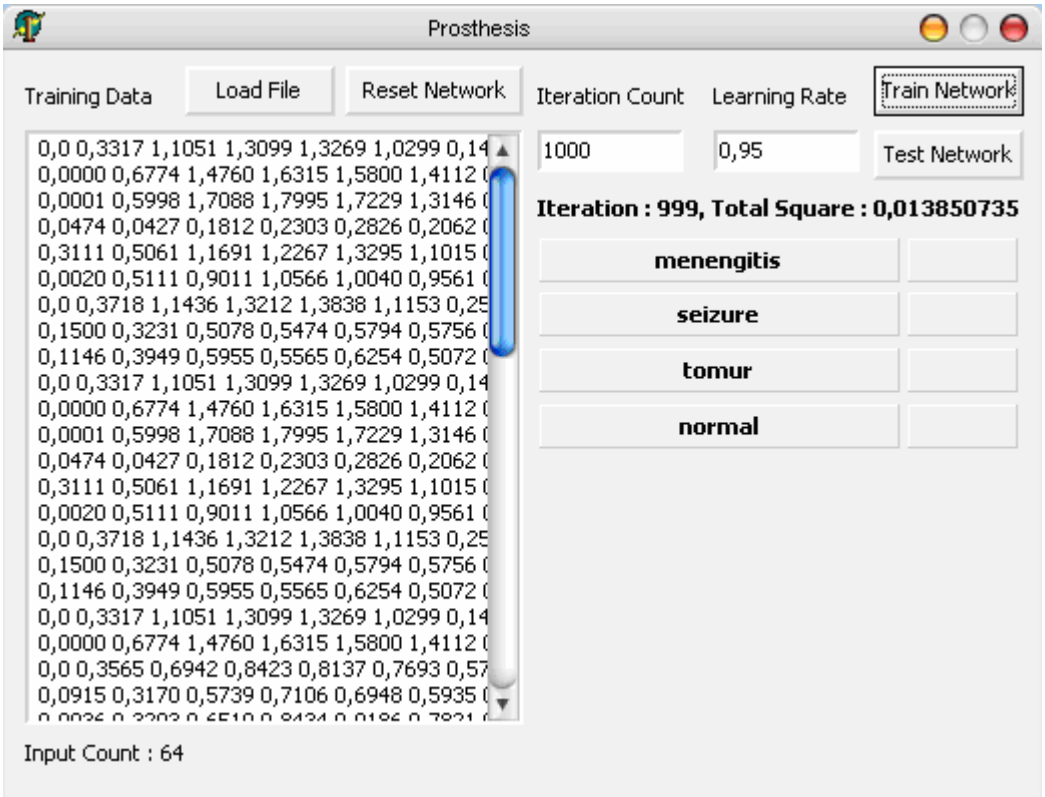
In the program, iteration number can be changed in the user interface. Training data is loaded by button “Load File” and “Train Network” button starts training. After training, again by “Load File” button testing data is loaded to the network. “Test Network” button tests the selected input data and displays the result.

Training

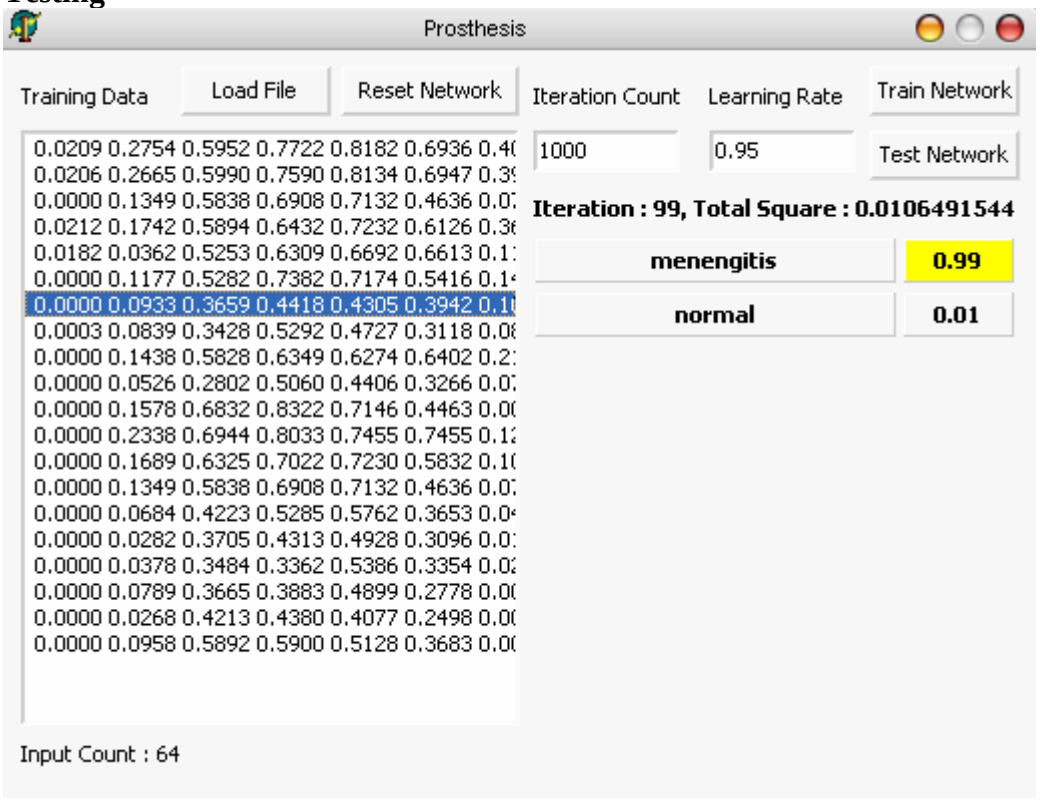

Prosthesis
Training Data
Load File
Reset Network
Iteration Count
Learning Rate
Train Network
1000
0,95
Test Network
Iteration : 99, Total Square : 0,0068712807
tomur
normal
Input Count : 64

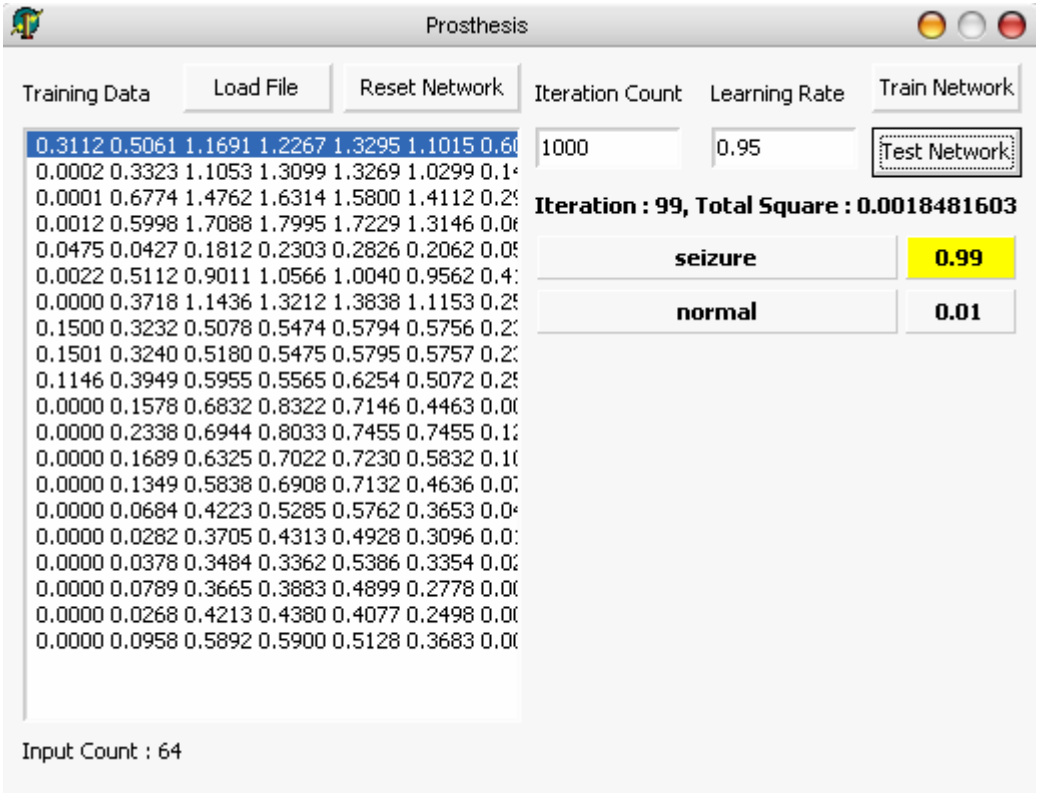

Prosthesis
Training Data
Load File
Reset Network
Iteration Count
Learning Rate
Train Network
100
0.95
Test Network
Iteration : 99, Total Square : 0.0106491544
menengitis
normal
Input Count : 64

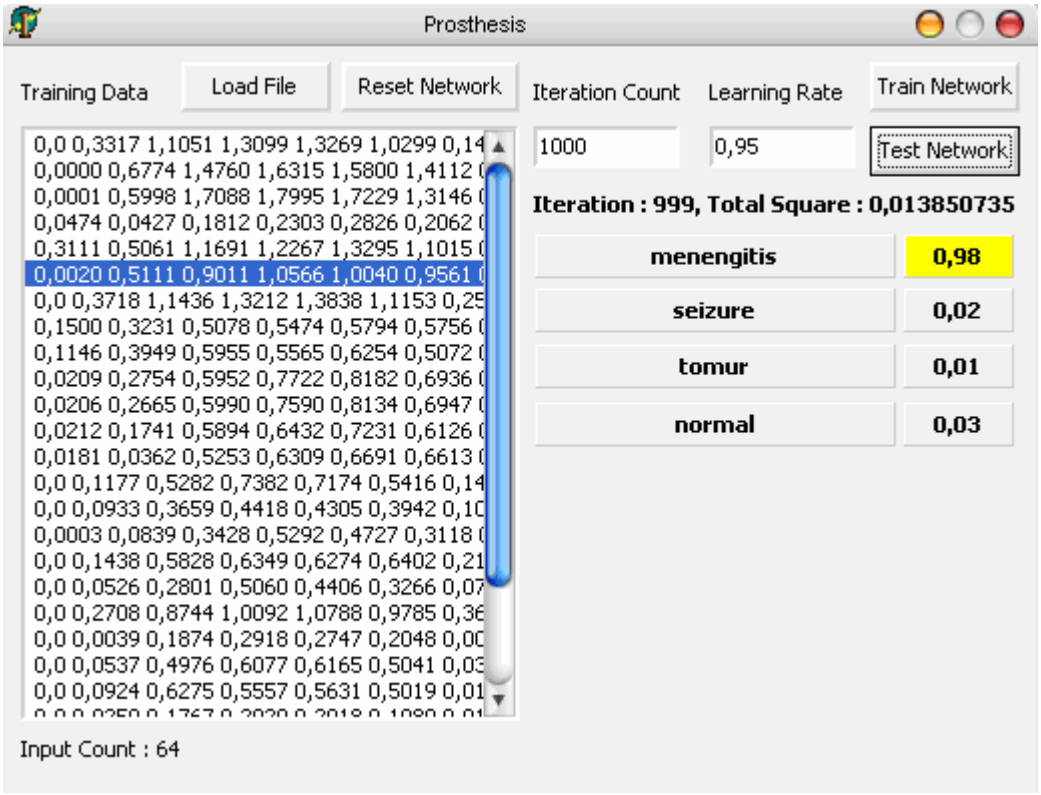

Prosthesis
Training Data
Load File
Reset Network
Iteration Count
Learning Rate
Train Network
1000
0.95
Test Network
Iteration : 99, Total Square : 0.0018481603
seizure
normal
0.0 0.3317 1.1051 1.3099 1.3269 1.0299 0.14
0.0000 0.6774 1.4760 1.6315 1.5800 1.4112
0.0001 0.5998 1.7088 1.7995 1.7229 1.3146
0.0474 0.0427 0.1812 0.2303 0.2826 0.2062
0.3111 0.5061 1.1691 1.2267 1.3295 1.1015
0.0020 0.5111 0.9011 1.0566 1.0040 0.9561
0.0 0.3718 1.1436 1.3212 1.3838 1.1153 0.25
0.1500 0.3231 0.5078 0.5474 0.5794 0.5756
0.1146 0.3949 0.5955 0.5565 0.6254 0.5072
0.0 0.3317 1.1051 1.3099 1.3269 1.0299 0.14
0.0000 0.6774 1.4760 1.6315 1.5800 1.4112
0.0001 0.5998 1.7088 1.7995 1.7229 1.3146
0.0474 0.0427 0.1812 0.2303 0.2826 0.2062
0.3112 0.5065 1.1693 1.2269 1.3298 1.1020
0.0020 0.5111 0.9011 1.0566 1.0040 0.9561
0.0 0.3718 1.1436 1.3212 1.3838 1.1153 0.25
0.1500 0.3231 0.5078 0.5474 0.5794 0.5756
0.1146 0.3949 0.5955 0.5565 0.6254 0.5072
0.0 0.3320 1.1051 1.3099 1.3269 1.0299 0.14
0.0020 0.6774 1.4760 1.6315 1.5800 1.4112
0.0 0.2338 0.6944 0.8033 0.7455 0.7455 0.12
0.0 0.1689 0.6325 0.7021 0.7230 0.5831 0.10
Input Count : 64

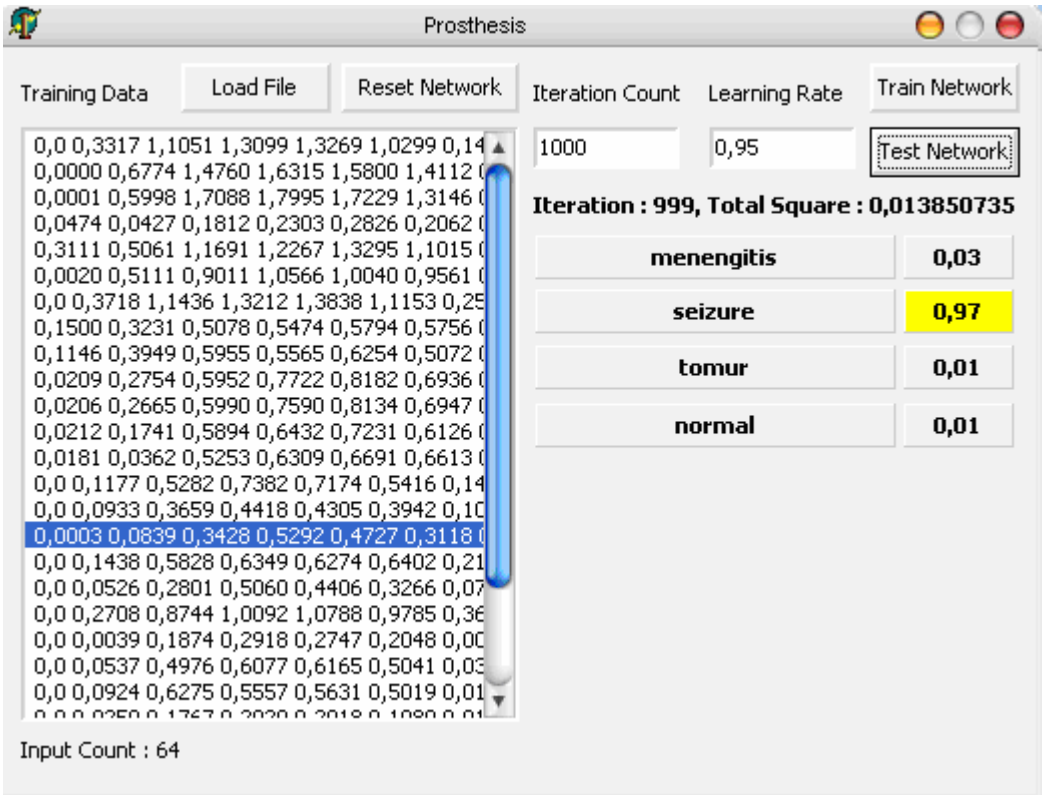

Prosthesis
Training Data
Load File
Reset Network
Iteration Count
Learning Rate
Train Network
1000
0,95
Test Network
Iteration : 999, Total Square : 0,013850735
menengitis
seizure
tomur
normal
0,0 0,3317 1,1051 1,3099 1,3269 1,0299 0,14
0,0000 0,6774 1,4760 1,6315 1,5800 1,4112
0,0001 0,5998 1,7088 1,7995 1,7229 1,3146
0,0474 0,0427 0,1812 0,2303 0,2826 0,2062
0,3111 0,5061 1,1691 1,2267 1,3295 1,1015
0,0020 0,5111 0,9011 1,0566 1,0040 0,9561
0,0 0,3718 1,1436 1,3212 1,3838 1,1153 0,25
0,1500 0,3231 0,5078 0,5474 0,5794 0,5756
0,1146 0,3949 0,5955 0,5565 0,6254 0,5072
0,0 0,3317 1,1051 1,3099 1,3269 1,0299 0,14
0,0000 0,6774 1,4760 1,6315 1,5800 1,4112
0,0001 0,5998 1,7088 1,7995 1,7229 1,3146
0,0474 0,0427 0,1812 0,2303 0,2826 0,2062
0,3111 0,5061 1,1691 1,2267 1,3295 1,1015
0,0020 0,5111 0,9011 1,0566 1,0040 0,9561
0,0 0,3718 1,1436 1,3212 1,3838 1,1153 0,25
0,1500 0,3231 0,5078 0,5474 0,5794 0,5756
0,1146 0,3949 0,5955 0,5565 0,6254 0,5072
0,0 0,3317 1,1051 1,3099 1,3269 1,0299 0,14
0,0000 0,6774 1,4760 1,6315 1,5800 1,4112
0,0 0,3565 0,6942 0,8423 0,8137 0,7693 0,57
0,0915 0,3170 0,5739 0,7106 0,6948 0,5935
Input Count : 64

Testing


Prosthesis
Training Data
Load File
Reset Network
Iteration Count
Learning Rate
Train Network
1000
0.95
Test Network
Iteration : 99, Total Square : 0.0106491544
menengitis
0.99
normal
0.01
Input Count : 64


Prosthesis
Training Data
Load File
Reset Network
Iteration Count
Learning Rate
Train Network
1000
0.95
Test Network
Iteration : 99, Total Square : 0.0018481603
seizure
0.99
normal
0.01
Input Count : 64


Prosthesis
Training Data
Load File
Reset Network
Iteration Count
Learning Rate
Train Network
1000
0,95
Test Network
Iteration : 999, Total Square : 0,013850735
menengitis
0,98
seizure
0,02
tomur
0,01
normal
0,03
Input Count : 64


Prosthesis
Training Data
Load File
Reset Network
Iteration Count
Learning Rate
Train Network
1000
0,95
Test Network
Iteration : 999, Total Square : 0,013850735
menengitis
0,03
seizure
0,97
tomur
0,01
normal
0,01
Input Count : 64

Sample input data for diseases

tumor1.jpg

```
0.0664 0.1193 0.5182 0.7833 0.7362 0.4799 0.1273 0.0680 0.0732 0.5579
0.7689 0.9013 1.3065 1.0753 0.6541 0.0877 0.2832 0.7042 0.7002 0.7868
1.5183 1.2494 0.8898 0.1999 0.4713 0.7253 0.7328 1.1790 1.9869 1.4012
1.0066 0.4816 0.6429 0.7673 0.6818 0.9988 1.7613 1.0866 0.9592 0.7245
0.6243 0.7033 0.3402 0.5845 0.9344 0.9923 1.0122 0.5224 0.3428 0.8021
0.6778 0.7335 0.8789 0.9467 0.9152 0.1468 0.0689 0.2510 0.5260 0.6220
0.6351 0.5127 0.1471 0.0663
```

meningitis1.jpg

```
0.0936 0.3203 0.6519 0.8434 0.9186 0.7821 0.5137 0.0999 0.2546 0.7446
0.7109 0.6916 0.7872 0.7439 0.7554 0.6011 0.4031 0.6456 0.7501 0.7698
0.7697 0.7469 0.7600 0.7822 0.6548 0.7621 0.7531 0.8648 0.9358 0.8526
0.8902 0.7738 0.7016 0.7326 0.7095 0.7376 0.9197 0.8322 0.7580 0.7563
0.6545 0.8250 1.1404 0.8301 0.8394 1.2173 0.9400 0.5639 0.4474 0.7709
0.9421 0.7815 0.8596 0.9360 0.7552 0.4002 0.0968 0.3350 0.4721 0.7068
0.7363 0.5061 0.4063 0.0967
```

seizure1.jpg

```
0.0    0.3317 1.1051 1.3099 1.3269 1.0299 0.1466 0.0    0.2180 1.4221
0.9206 0.9537 0.9494 1.0322 1.5252 0.0586 1.2110 0.9688 0.8481 0.8717
0.8522 0.9317 1.1592 0.8952 1.3940 0.9504 0.8805 0.9142 0.9231 1.0073
1.0666 1.3961 1.2600 0.8836 0.8997 1.0275 1.0142 0.9422 1.0265 1.2902
0.9415 1.0522 0.8782 1.1314 1.0834 0.9003 1.0678 1.0710 0.0968 1.5540
1.0251 0.9850 1.0765 0.9507 1.5714 0.2959 0.0    0.1751 1.0589 1.3710
1.4786 1.2643 0.4145 0.0
```