BREAST CANCER HISTOPATHOLOGICAL IMAGE CLASSIFICATION USING NEURAL NETWORK

A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCES OF NEAR EAST UNIVERSITY

By
NURDEEN NATFA

In Partial Fulfilment of the Requirements for the Degree of Master of Science in Electrical and Electronic Engineering

NICOSIA, 2017

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last name: NURDEEN NATFA

Signature:

Date:

ACKNOWLEDGMENTS

I would like to express my deepest thanks and sincere appreciation to my supervisor in this work, Assistant Prof. Dr. Kamil DIMILILER; who was my motivator during the work of this modest thesis. It is time to thank him for all his patience and guidance throughout all my study for my master degree. Prof. Dimililer's knowledge and critics were very important to put me on the right way and to enlighten my ideas and inspired me with new thinking manner. My deepest gratefulness is expressed also to all my family members, and my wife who was my great fan and supporter. I will always be grateful to my dear friends, colleagues, and the Libyan community in the TRNC.

To my parents and family….

ABSTRACT

Breast cancer is one of the most famous types of cancer that affect the women during the last decades. According to medical statistics, 12.6% of women around the world are subject to this type of cancer. The disease is very dangerous and causes the death of a lot of women. However, it is medically possible to treat it totally if it is detected in its early stages. The early detection of breast cancer is one of the most important cure systems that can save the lives of millions of women around the world. Periodic check is one of the main methods of detection of the breast cancer. However, the lack of experience of many women and the lack of specialized medical centres in many areas around the world makes it difficult to be achieved completely. Artificial Neural Networks are very famous for their huge capabilities to simulate the human brain. They have been used in many medical fields for disease detection and classification. They are also implemented in different medical instruments to help medical experts to identify the diseases. The use of ANN structures for the early detection of breast cancer is one of the promising projects to save lives of women around the world. This work will concentrate on the implementation of ANN for the detection of infected tissue of the breast with breast cancer. Database of the disease images will be collected throughout this work, processed, and used with artificial neural network. Practical results will be collected, printed, and discussed as well.

Keywords: Artificial networks; back propagation; breast cancer; malignant tumor; benign tumor

ÖZET

Son yüzyılda, kadınları etkileyen en çok bilinen kanser türlerinden biri göğüs kanseridir. Tıp statistiklerine göre, dünya kadınlarının % 12.6'sı bu kanser türünden muzdariptirler. Hastalık tehlikeli ve de bir çok kadın için ölümcüldür. Erken tanı sayesinde tam tedavi edilebilir. Göğüs kanserinin erken teşhisi, milyonlarca kadının hayatını kurtaracak en önemli safhadır. Göğüs kanserinin teşhisinde periodik kontroller en temel yollardan birisidir. Fakat, bir çok kadının bu konuda deneyimsiz oluşu ve dünyanın bir çok yerinde olmayan uzman tıp merkezleri nedeniyle bu konuda hedefe varmakta zorluklar olmaktadır. Yapay Sinir Ağları insan beynini simule etme konusunda çok büyük bir yeteneğe sahiptirler. Hastalıkların belirlenmesinde ve sınıflandırılmasında bir çok tıp merkezlerinde kullanılmaktadirlar. Ayrıca, tıp uzmanlarının hastalığı teşhisinde değişik tıbbı aletlerde de uygulanmaktadır. Göğüs kanserinin erken teşhisinde ANN, kadınların hayatlarını kurtarma konusunda yapılan ve ümit vadeden projelerden birisidir. Bu çalışma, ANN'in daha fazla, göğüsteki bakterili dokuyu ve göğüs kanserinin teşhisinde kullanılmasına ağırlık verecektir.

Anahtar Kelimeler: Yapay sinir ağları; geri yayılım; göğüs kanseri; büyüyen tümör; kötü huylu tümör

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LIST OF ABBREVIATIONS

ANN: Artificial Neural Network

CNN: Convolution Neural Networks

MSE: Mean Squared Error

CHAPTER 1

INTRODUCTION

1.1 Introduction

Cancer is a well known and spread public health problem around the world. According to medical care agencies, in 2012 approximately 8.2 million death were caused by cancer. The number is horribly increasing and expected to become 27 million by 2030 (Spanhol, Oliveira, Petitjean, & Heutte, 2016). Breast cancer is one of the most mortal cancer type among women. Most of the death caused by breast cancer is mainly due to the wrong or late evaluation of the cancer. Early detection of breast cancer is the key factor for the protection and survival of a woman who is affected by breast cancer (Singh, Surinder, & Dharmendra, 2016). Breast tumor is screened nowadays using mammography and X-Rays screening. Microwave detection is also being used for the detection of breast cancer tumor. Although a lot of researches are being carried out yearly about the roots of the breast cancer, no evidences have been found revealing the main causes of the disease (Ahmad, Isa, & Hussain, 2013).

Scientific and medical researches revealed that the early detection of the cancer tumors increases significantly the hope of curing patients (Jayaraj, Sanjana, & Darshini, n.d.). The treatment of the cancer is also based on the kind of symptoms that must be classified accurately. The main and most important classification of the cancer is to decide whether the tumor is benign or malignant. In the case of benign tumors, the treatment is used with smaller amounts. This is mainly because the higher chances of patient survival. The malignant tumor on the other hand is more concerned by the strong treatment without considering the side effects (Tripathy, 2013). For this reason, the correct detection and classification of cancer type is a very important issue that can save the lives of millions of women.

Mammography is one of the important and most famous early detection techniques for breast cancer. Mammogram images are in general studied and analyzed carefully by specialists to observe the disease in its early stages. Converging patterns of the tissue and vessels are described using mammograms. Any deviation from these patterns in mammogram is viewed carefully and considered as possible cancer tumor.

Machine learning is one of the most promising breast cancer detection techniques (Jayaraj et al., n.d.). It can offer a potential support for medical doctors to evaluate faster and more accurately the tumor type. The use of artificial intelligence and machine learning can offer a very cheap, fast, easy, and accurate method for tumor kind detection. An intelligent system provided with enough information can assist also medicines in the classification and evaluation of the infection type.

Artificial neural networks are widely used nowadays in different science fields. They present a powerful tool that can work and learn the same way human brains do. They have the potential to generalize patterns and learn using examples. Development of digital processing technologies is increasing the power of the artificial neural networks. Fast computers with enough memories can perform very complex recognition and classification tasks in an accurate and fast manner.

This work proposes the use of artificial neural networks in the classification of histo-pathological breast images. The classification will be based on the type of cancer tumor in the first stage into benign and malignant cancer. The next step will be used to find out the type of the benign and malign cancer. For this reason, database of pathological images is collected and going to be used with our system. The database is divided into two parts, benign and malignant cancer. Each one of these is also divided into four sub divisions dependent on the type of tumor. Images were collected using a microscope with different zooming settings.

1.2 Literature Review

The breast cancer has attracted the attention of medical doctors, laboratory specialists, scientists, and image processing researchers. It is a common background of research for all these specialists as its study requires the collaboration of them to obtain the best results. In (Spanhol et al., 2016) the authors used 7909 histo-pathological images of breast cancer acquired from 82 patients. This dataset contained malignant and benign images. The authors presented a database called BreakHIS that represents a large amount of microscopic images that is not easily present in public domain. A baseline pattern recognition system was then proposed. In (A., S., Caroline, & Heutte, 2016) the same dataset was used with ANN for breast cancer images classification. The dataset was divided arbitrarily into 70% for training and 30% for test of the neural network efficiency. In the same work, SVM classification was also applied and the results were compared with the ANN results. An artificial neural network system for false alarm detection of in microwave breast cancer detectors was introduced in (Singh et al., 2016). In this work a simple human breast model was built with a tumor of 5 mm size to examine the microwave detection. In (Ahmad et al., 2013) a hybrid classifier composed of genetic algorithm with artificial neural networks was proposed for the study of breast cancer. The aim of the work was the improvement of the early detection systems of breast cancer. The efficiency of the proposed method was reported to be 99.43% maximum and 98.29% average.

In (Pastrana-Palma, 2016), a study of the use of the ANN classification system with digital mammographic images was presented. The obtained efficiency of the reported job was approximately 80%. A pattern recognition approach for breast cancer detection and classification was applied and presented in (Hassan, Mariam, Adnan, Gilles, & Leduc, 2016). The pattern recognition in this work relied on the use of the well known artificial neural networks. The work reported an accuracy of 99.3% of the training set. In (Jayaraj et al., n.d.), the authors have presented a review of the breast cancer detection literature. Different works were discussed and there accuracies were presented.

1.3 Methodology of the Work

In this work, the classification of the breast cancer images will pass by different steps. These steps are subdivided into image processing and artificial neural classification. The first step will concentrate on the reading of the different images and feature extraction of these images. Processing of images will include the reading of the pnj images and converting them into gray scale images for simplification of calculations. The gray images are then going to be filtered using a suitable filtering method to extract the original pure image and reject the noise. After filtering, images will be divided into two parts; the first for training and the other part will be used for test of the network. Two different networks will be used. The first will be used to separate the images into malignant and benign tumor images. The second network will classify the separated images into different four types. **Figure 1.1** and **Figure 1.2** below show a sample of the database that is going to be used in our work. **Figure 1.3** resumes the flowchart of the proposed work.

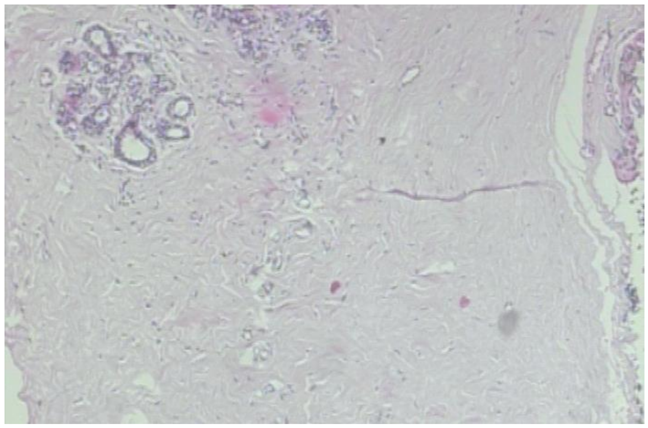


Figure 1.1: Sample of the mining tumor image.

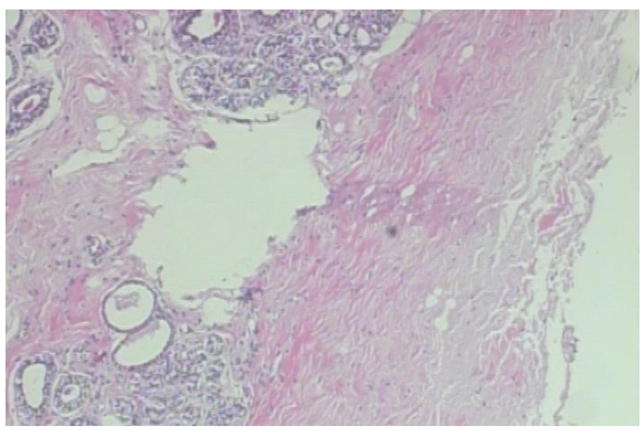


Figure 1.2: Sample of the malignant tumor image.

Figure 1.3 below presents the flowchart of the proposed work. The first step of the work is the database collection that will be followed by processing the database images. The image processing includes applying Median filter, segmentation, and image resizing. The next step of the work is to build the targets of the ANN structure, build the ANN structure, and start the training of the network. Upon the end of the training process, a test step will be applied.

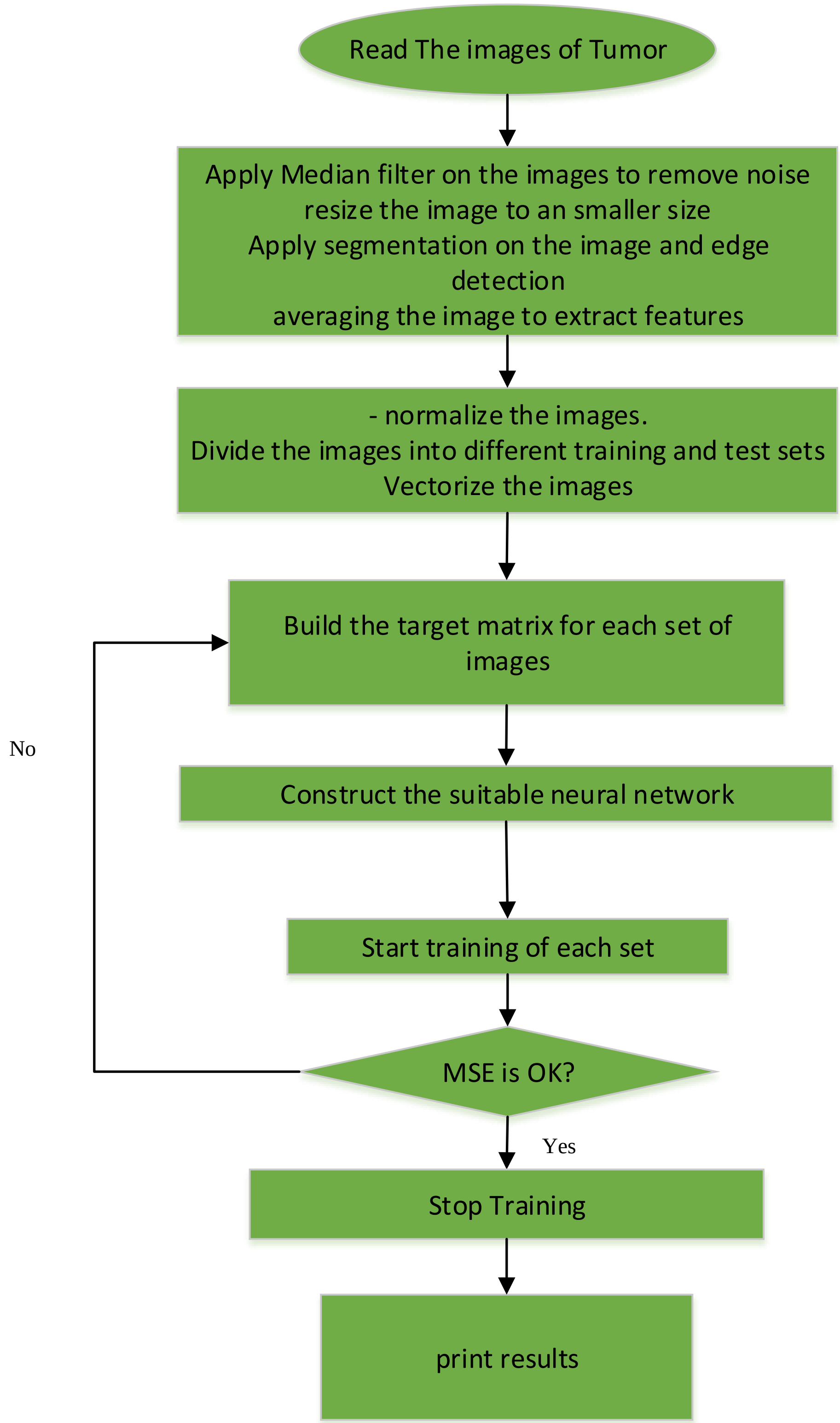


Figure 1.3: Flowchart of the proposed methods

CHAPTER 2

IMAGE PROCESSING TECHNIQUES

2.1 Introduction

Computer images have become famous term in the sciences and public life. It opens the door for connection with the external world by exchanging data through internet and computer appliances. This process is a totally digital or can need the intervention of human being. Computer vision term signifies that the process doesn't need any human intervention. Thus the whole process will be applied automatically by a digital processor and computers. Different topics can be involved in the computer vision process such as image analysis. Image analysis is another process that includes different subjects and extends for more wide research.

Image processing is a different subject that involves the human being touch in processing the image. It has also many subjects involved, these topics include image restoration, image enhancement, and many other processes. For better understanding of these different processes, it is important to study the human vision system to generate a deep idea about its function and properties. This chapter is intended for the study of human visual system and its main characteristics. Different image processing techniques will also be treated in the course of this chapter to build better idea about these techniques.

2.2 Human Visual System

Human visual system is something that we use unconsciously. Humans never think of the effect of makeup on the physiological systems vision. It is important to discuss the understanding of the process of distinguishing visual data. This discussion will allow for better understanding of different methods implemented in image processing.

Human visual system is composed of two main interconnected parts; the eyes that are used for capturing visual scenes and the brain that process the images, classify, and recognize them. These two parts of the human visual system are connected between each other via nervous links. The human eye is considered as a perfect imaging sensor with good resolution and structure. The human brain is a super powerful processing system. Optic nerves are connecting these two components and ensure the information transmission between them. The human vision system works in a very précised manner. Eye lenses receive light reflected from the objects in the zoon of our vision. These lights are focussed with the help of lenses and directed to the retina of the eye. The retina contains a huge number of visual sensors that sense the light intensity. The sensors respond to the light intensity by electrical chemical reaction. This reaction generates an electrical signal that flows through the nerves to the brain. From it side, the brain has the ability to create a pattern from the collected signals. This pattern is distinguished as an image by the brain.

The visible light by the human eye is limited because the eye doesn't respond for all light energy and wavelengths. The wavelength that are situated in the range of 380-825nm can be captured while the retina of the eye can't sense other lights. In image processing, the spectral of images or light is divided into different bands based on the wavelength of the light. The blue spectrum has a wavelength of 300-400 nm; green has a wavelength of 500-600 nm; while red has a wavelength of 600-700 nm.

The eye in its structure has two different sensor types or photoreceptive cells. Both of these types receive falling light and translate it to electrical signals. This process passes through electrochemical reaction to be accomplished. The receptors are known as cones and rods. They are scattered on the retina which is the back side of the eye.

2.3 Image and Image Representation

In digital image processing, digital image is stored and processed in the form of two-dimensional group of numbers. Each number of these values is called pixel and corresponds to the intensity or brightness of the image at a given point. This arrangement is know in mathematics as matrix.

The single matrix image can contain data of the image intensity for one colour and thus it is known as monochrome image. Such images are known in the DIP by gray scale images. there are different other types of images where more information is required for better representation of the pixels such as binary images, colour images, RGB, and multi-scale images.

Figure 2.1: RGB image, gray image, and binary image of tissue

2.3.1 Binary Images

Binary images can be considered as the most basic shape of images. From the name it can be understood that they can take binary values of one or zero. Each pixel in the image is represented by a one bit binary value. The colour can be either white or black. Binary images are known by 1 bit/pixel rate for that reason. They are used in applications where the only required information is the shape without details. They can be implemented in deformation inspection of products. The binary image is normally generated by threshold process where the pixel value is considered true if it is more than a given threshold and zero if it is less than that value.

2.3.2 Gray-Scale Images

These are the main example of monochrome images or single colour images. the pixels in the image contains the brightness of the image only without any information about the spectral analysis of the light. The brightness levels are function of the bit rate of the gray scale image. In an 8 bit image, there are 256 different brightness levels. In a 16 bit image the number is raised up to 255^2 different levels. Typically, general images use 8 bit system and thus are represented by 256 levels of white and black colours. This type of images is useful and easy for digital computers as it uses the byte in its pixel representation which is the small standard unit in computers. In higher accuracy applications like medical purpose images or astronomical images; high resolution of 12 or 16 bit/pixel can be implemented. These high resolutions are useful in the zooming of the image. This process can show details that couldn't be seen with normal resolutions.

2.3.3 Colour Images

Coloured images are represented as multi band monochrome image information. In this representation, each band of information matches with a unique colour. The real information accumulated in the image is the level of the brightness of each colour or band. In case the image is presented, the resultant brightness level is presented on the monitor by picture pixels with the same intensity of the correspondent colour. Typically, colour images are characterized in the form of R (red), G (green), and B (blue) colours. Using the 8 bit single colour paradigm, the destination colour image will have 24 bits in each single pixel.

In many applications, RGB colour information is converted to another form of mathematical model. In such models, the image is converted to one dimensional brightness matrix and another two dimensional colour space. The last contains information about the relative colour intensity rather than intensity.

HSL (hue, Saturation, Lightness) transform gives a description of colours in other way. The hue is a description of how we see colour, the saturation is a measure of the white ration in the colour, while brightness describes the intensity of light. This transform is actually built to suit the human perception of colours. We can build a picture by describing the three values of hue, saturation and brightness.

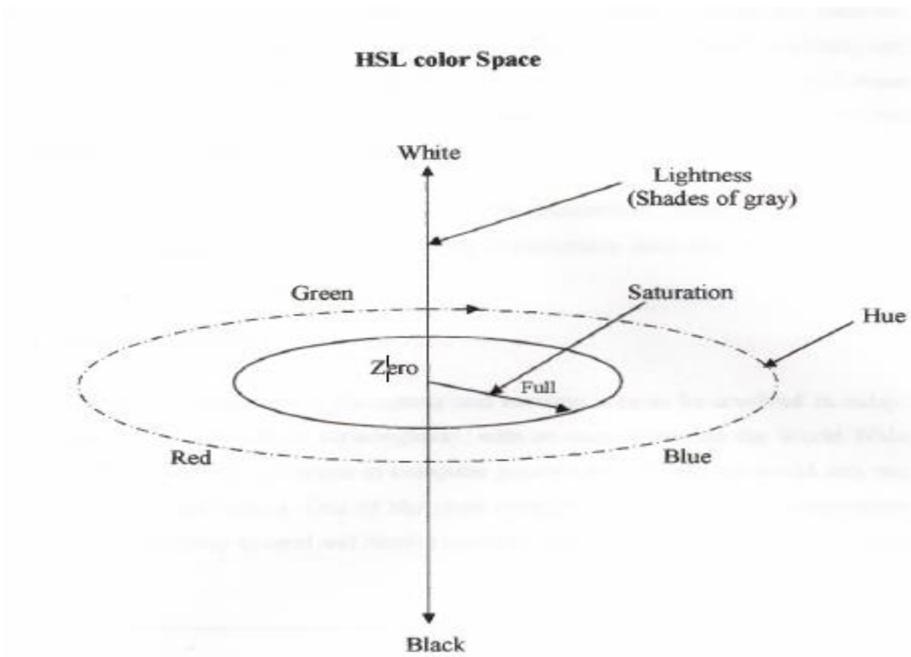


Figure 2.2: HSL colour image space

2.4 Image Processing

Image processing is the science of treating the images properties under the supervision of human. After the treatment of the images, they should be controlled by humans to ensure it is acceptable. To understand better the image processing techniques, understanding the human visual system is a must. The main processes of image processing are image compression, image enhancement, and image restoration.

Image restoration is known as the treatment of images that have some estimated or known degree of degradation. These images are taken and restored to their initial state before degradation. It is used in image photography or in fields of publications where image needs to be visually perfect before being published. In such applications it is important to have an idea about the type of degradation in order to be able to restore the image. This helps in creating a model for the distortion in order to be able to apply its inverse on the image. The inverse model of degradation will restore the distorted image to its initial and original state.

In the process of image enhancement, a normal image is processed to be improved even if it is originally not distorted. This is done with help of the response of human visual system. A simple and efficient enhancement method is the contrast stretching of the image.

Enhancement techniques are more likely to be problem oriented. This means that the method that is used for satellite images enhancement can be unsuitable for medical images enhancement. Despite the fact that enhancement and restoration are alike in purpose, to ameliorate the vision of the image, they use different approaches to solve the problem. In restoration, the process aims to model the distortion in order to inverse its effects. Whereas, enhancement investigates in the human visual system experience to visually improve the image quality.

The image compression is a totally different process in which the massive data of an image is stored in smaller space of data. This is mainly achieved by eliminating visually unnecessary data and make benefit of data redundancy in the image. Over more, computer applications and digital vision systems doesn’t need every detail of the image. They can make better use of compressed images.

2.4.1 Image Segmentation

Image segmentation is imperative in many applications. It is useful in different computer assisted processes and image processing techniques. The segmentation of an image aims at extracting the meaningful parts of an image and splitting the images into regions of interest prior to the processes of higher levels. These processes include objects identification, image classification. In reality, segmentation is very useful in finding any detail in an image.

Image segmentation techniques search for items that gain some amount of homogeneity or have some match with their edges. Almost all segmentation techniques represent modification, or combination of these two aspects. The measures of contrast and homogeneity can include characteristics like level of gray, colour profile, or texture.

2.4.2 Filtering Techniques

Filtering is a procedure for image modification or enhancement that is implemented used to highlight some features or to take rid of some other features. Image filtering is an operation known by neighbourhood operation. Such operations indicate that the pixels value is determined in function of the surrounding pixels. Special algorithms are applied on the neighbouring pixels to evaluate the perfect value of the pixel. Some common filters are Sobel filter, Laplacian of Gaussian, Unsharp filter, average filter, median filter, and wiener adaptive filter. In this work, we are going to apply wiener adaptive filter for the enhancement of the images.

2.4.2.1 Wiener Filter

Wiener filter is considered as one of the most important techniques in removing noise from digital images. Wiener filter uses an estimation of the noise level in the noise removal process (Frank, Floyd, Wilfredo, & Kincaid, 2014). Wienerr filter is able to work on noisy distorted images better than any other filters. Wiener filter is defined by:

$$W_f = \frac{|H^2|}{H * |H^2| + k} \tag{2.1}$$

Where H defines the fast Fourier transform of the noise model and k is a scalar constant. After applying wiener filter on a noisy image, the filter removes the noise from it and restores it to an original shape. **Figure 2.3** below shows the effect of adding noise to an image and removing the noise using wiener filter.

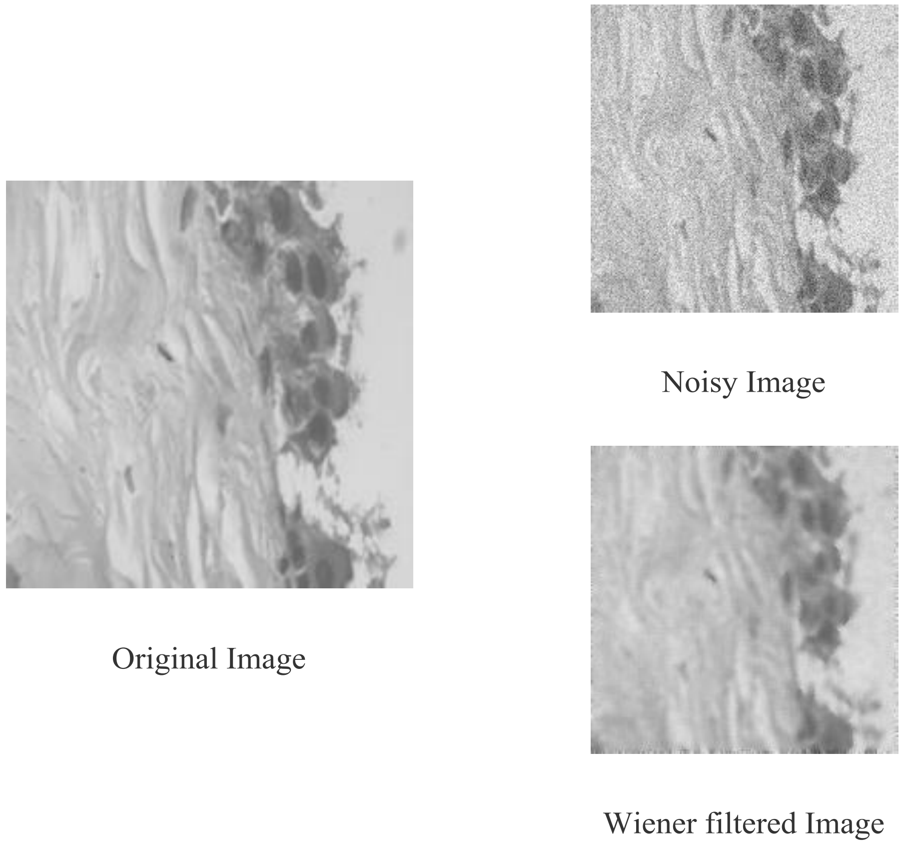
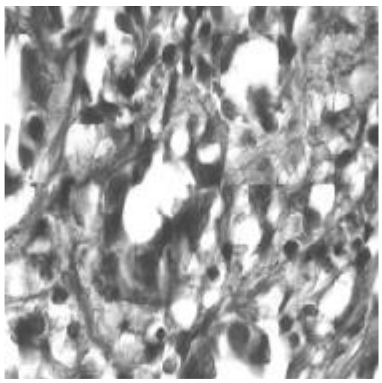


Figure 2.3: Wiener filter for image restoration

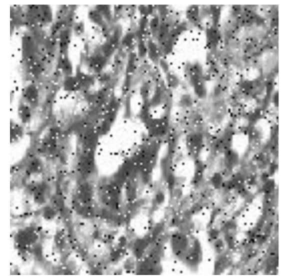
2.4.2.2 Median Filter

Median filter is implemented to decrease the noise levels in the images where there are impulsive noise types. It creates clear image and less concentration in the image pixels. The main idea in the median filter is to make rid of the strange pixels values within a window of the image. Any strange value is eliminated by choosing the median value within the cluster of pixels and fixing it in the centre; the cluster moves ahead and repeats the process until all pixels are replaced by the median of their surrounding clusters.

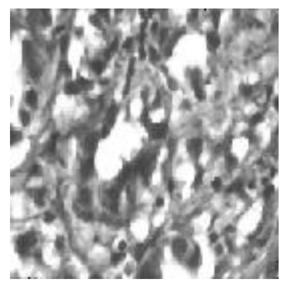
The process of applying the median filter is very simple. A window around the required pixels is defined and its statistical median value is found. This value is simply used as replacement of that pixel value. The process continues replacing the pixels with their surrounding median until all pixels are processed. This way; all pixels with values that are too far from their neighbourhood are replaced with pixels that are similar. **Figure 2.4** below presents the results of image filtering using median filter. The figure shows how the median filter removes the dots in the image.



Original image



Noisy image



Median filtered image

Figure 2.4: Median filter for image filtering

In this work, different image processing techniques were used and applied on the images of the tumor. The image processing phase included the next operations:

1- Reading the RGB images of the tumor.

2- Converting RGB images to Gray Scale images.

3- Applying Median filter to remove noise from images.

4- Segmenting the images by using the edge detection.

5- Resizing the image to reduce the data processed.

6- Converting the 2D image to 1D vector that can be fed to the neural network.

7- Normalizing the pixel values of the image.

The image processing program was coded using MATLAB software in **Figure 2.5** ; the figure below presents the execution of the processing code during the image processing. The original image of the tissue is presented in the **Figure 2.5.** This image contains information about three colour spectrums. It is actually less useful for computerized processes**. Figure 2.6** presents the gray scale image obtained from the previous image. It contains data about the level of the gray colour in the form of 8 bit digital number. This level is presented on a scale of 256 levels. The higher the gray level the whiter the image is. The level zero corresponds to the black. **Figure 2.7** presents the grades of gray level image.

Figure 2.5: Execution of the image processing code

The manipulation of gray scale images is easier and less memory consuming than the RGB images with similar performance in computerized processes. The image matrix can be easily processed in gray scale images. Most of filters can be applied on single colour images like greyscale images. In our work, the Wiener filter was applied on the gray scale image to remove any type of noise that can be contained in within. **Figure 2.8** represents the filtered image of the tissue. This image was segmented using zero crossing edge detection method. The edges were detected and the resultant image is shown in **Figure 2.10**.

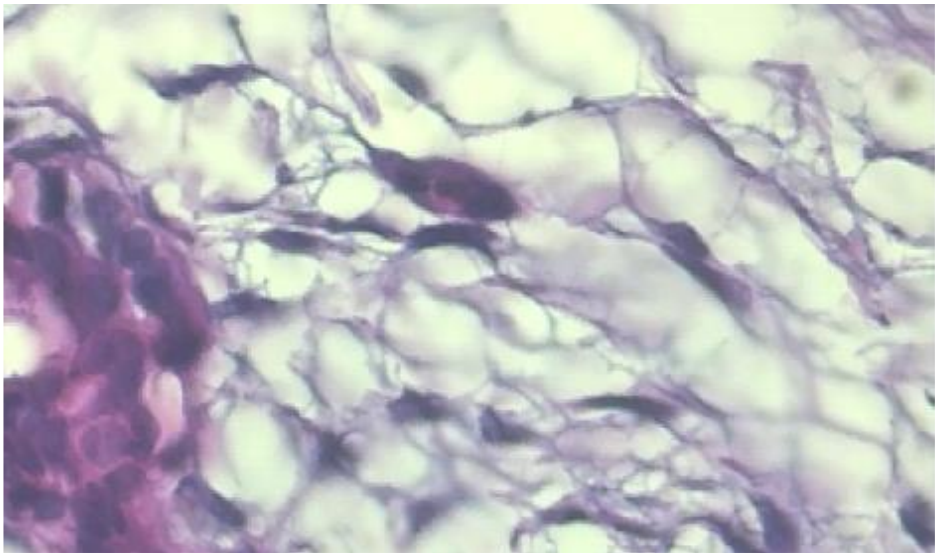


Figure 2.6: RGB image of the tissue before being processed

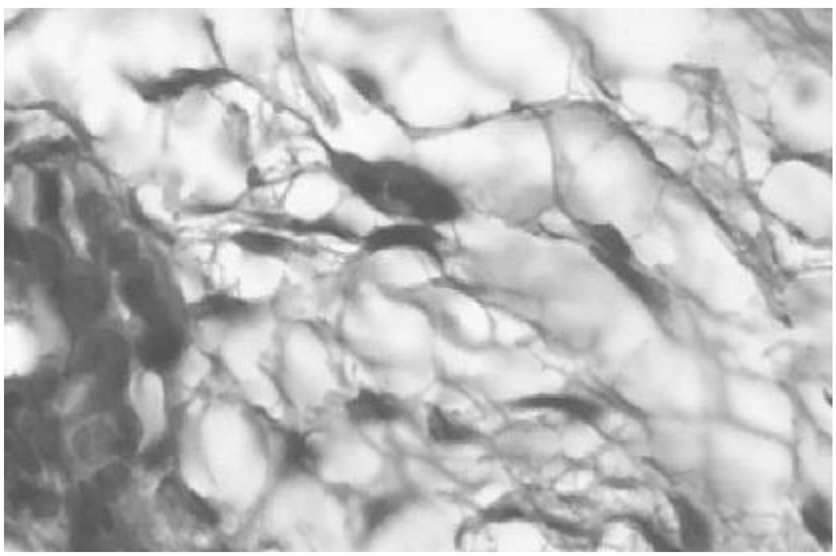


Figure 2.7: Gray scale image of the tumor tissue

Figure 2.8: Gray scale level from zero to 255.

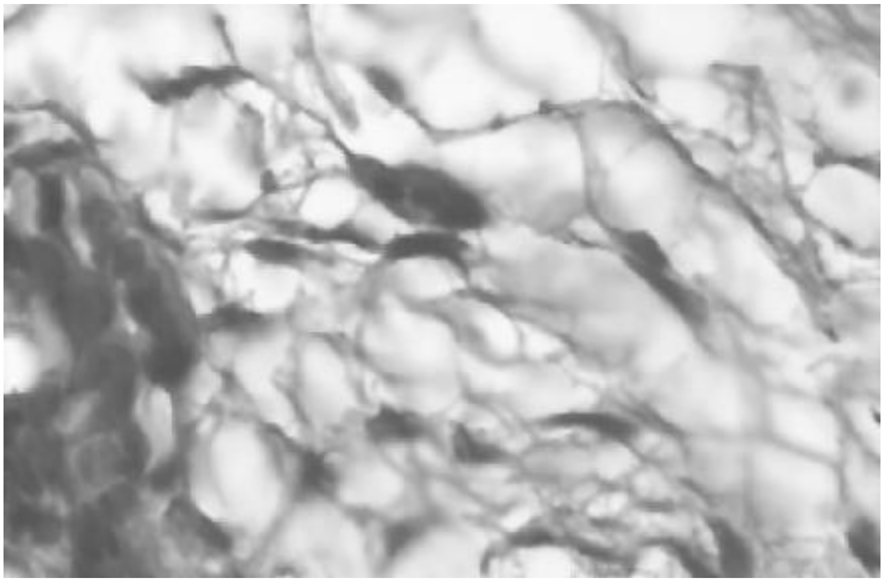


Figure 2.9: Gray scale image after being filtered using Wiener filter

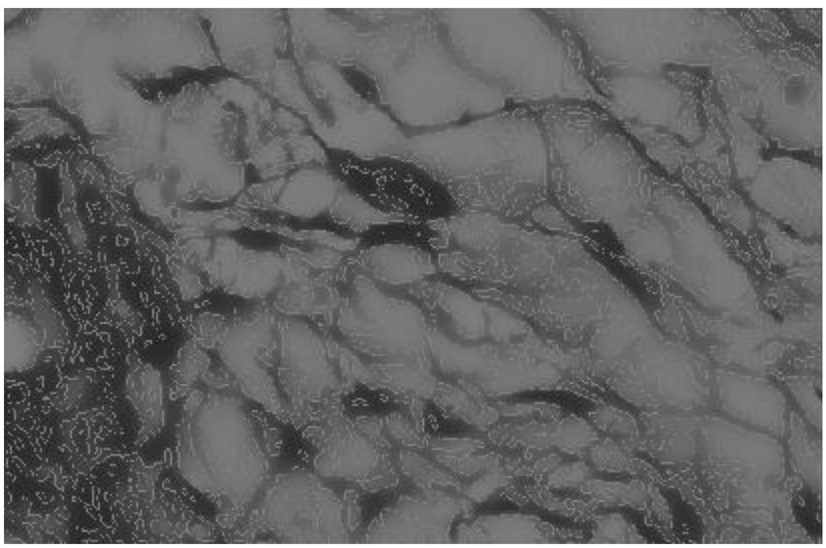


Figure 2.10: Segmented image of the tissue

After detecting the edges and segmenting the image of the tumor tissue, this image is then down scaled to reduce its size. The small size image is more suitable for the use with artificial intelligence applications. All the details of the image can be contained in smaller version of the image. **Figure 2.11** above shows a sample of the small images of the tissue.

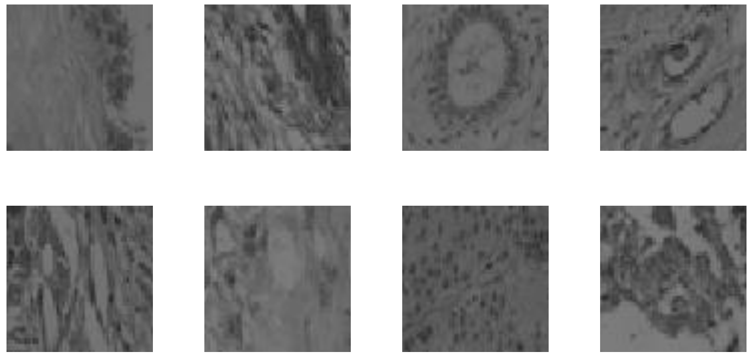


Figure 2.11: Final Processed images of the tissue

CHAPTER 3

ARTIFICIAL NEURAL NETWORKS

3.1 Introduction

Artificial neural networks are special structures designed for the imitation of the function of biological nervous system. They have the ability to learn patterns based on different examples and to model relations between different systems. This chapter will introduce the artificial neural networks and discuss their basic structure.

3.2 Early Neural Networks

The idea of the neural networks has started early in the forties of the last century. A paper entitled “A logical calculus in the ideas immanent in nervous activity” was published by two scientists. These were Warren Mcculloch and Walter Pitts. The main idea in their published paper was about the modelling of a system similar to the human nervous system. Their model represented a mathematical model that was called later neuron. Their neuron had the ability to receive and input and generate a suitable output (Colin, 1996).

The output from this simple neuron was a logical output that has one of two choices. It had the ability to collect the inputs and decide whether they have enough power to activate an output or not. When the received input reach certain level which is called threshold, the output is activated; otherwise, the output is deactivated. More complex networks can be formed by combining huge number of single cells of the same type. They will be activated or deactivated the same way single neuron does. The theory created by pitts and Mcculloch was very interesting and some types of networks are still named after their names.

The idea continued the same way during the 50s and 60s with small modifications. The concept of perceptron was introduced in the field by the French psychologist Frank Rosenblatt in the year 1958. The idea of perceptron was simple and made use of single neurons to create a network. This network was interconnected to analyse data and information. Different publications on the perceptron and neural networks were published until the beginning of 80s. the main problem facing the perceptron was how to solve some complex types of relationship s between input and output data (Cios & Shields, 1997).

In the year 1962, Rosenblatt was able to create a teaching process that guarantees the convergence of the error function. His algorithm was an adjustment of the weights inside the recognition loop during the teaching process. The process updates the values of the weights until generating suitable outputs. The challenge for this system was mainly the slow and weak computers of that time that were used just for very special applications and cost a lot of money.

The cognition system was the early model of many layers networks. Such networks had a very efficient learning process. The system construction, connections, and weights changed between a structure and another. In 1982 Hopfield's networks were created and implemented to propagate data in two directions(Minsky & Papert, 1969). The use of the back propagation process for the learning of ANN was the main inspiration for the incorporation of the ANN in the 80s. This process relies on the propagation of the error values through the different layers of the neural networks. This error is used to evaluate the weight values and generate new values for them. Since then, many different updating theories were proposed to guarantee the minimization of the error signal after the weight updating process (Anderson & McNeill, 2010).

3.3 The Biological Neurons vs. Artificial Neurons

The brain is a huge computer composed of millions of millions of interrelated nerves. Each one of these nerves is a biological cell in which different chemical and electrical processes are happening endlessly. These processes are the main reason for the creation and transmission of information and ideas. Each one of the nerves is connected to thousands of surrounding neurons. At the moment any one of these neurons fires, an electrical signal arrives at the dendrite. The entire received signals are collected and accumulated together. The accumulation can occur in spatial or temporal domain. The total input received at the dendrite is then transmitted to the soma of the cell. The role of the soma is to provide the required maintenance for the cell parts. The nerve fires just if it’s received signal is enough and able to fire. It is accepted that the output strength is constant whatever the strength of the input if it is greater than the threshold. The output strength of output is also constant at all parts of the cell. The synapses ensure the transmission of the signal from a neuron to the next neuron (Cios & Shields, 1997). **Figure 3.1** presents the elements of the biological neuron**. Figure 3.2** illustrates the shape of the synaptic connection between two successive neurons.

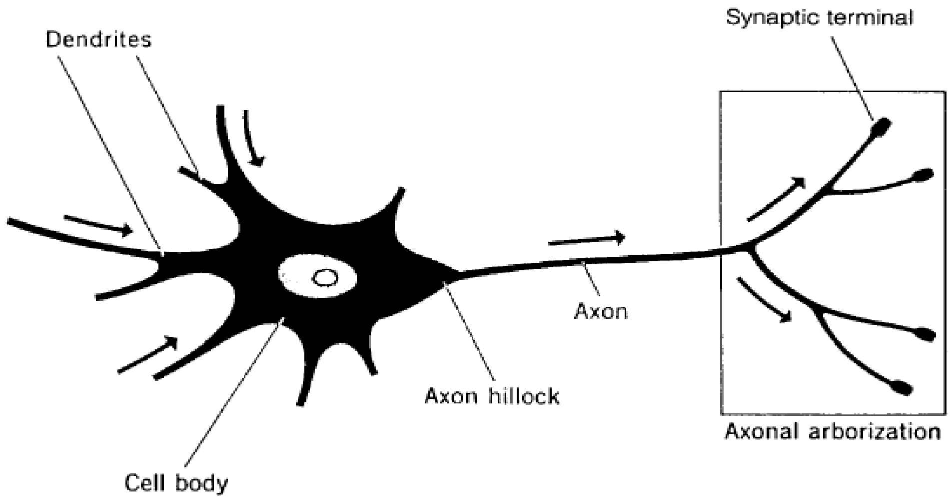


Figure 3.1: Structure of the biological nervous cell

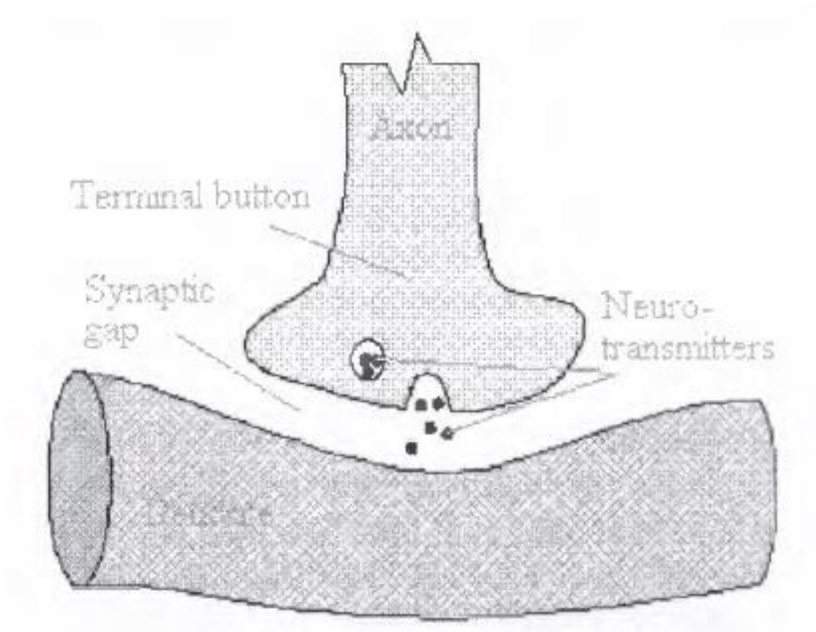


Figure 3.2: The synaptic connection between two neurons

3.4 Artificial Neural Networks

Neurobiologists have created sophisticated mathematical reproduction of biological neurons That can be used in computers. Their model was very helpful in performing simulations of the thinking process and to imitate the brain function. In electronics and computer sciences, the interest is more consisted toward the uses and characteristics of such model. Simpler neurons or neural models can be implemented in computer sciences as far as they present satisfactory solutions for the different problems. While attempting to imitate the functions of the human brain, scientists have built electronic circuits that had the ability to simulate the neural networks. However, modern computers offer high flexibility in simulating the neural functions and offering high performance artificial neural network (Colin, 1996).

The main element of a neural network is known as a node. The node receives its signals from the other connected nodes or even from another source or sensor (Khashman & Dimililer, 2007). Every single input is connected to a related weight or factor. The weights can be changed to simulate the learning in the synapses. Each unit has a function that is used to find the sum of its inputs after being multiplied by the weights. The structure of the node is presented in **Figure 3.3**.

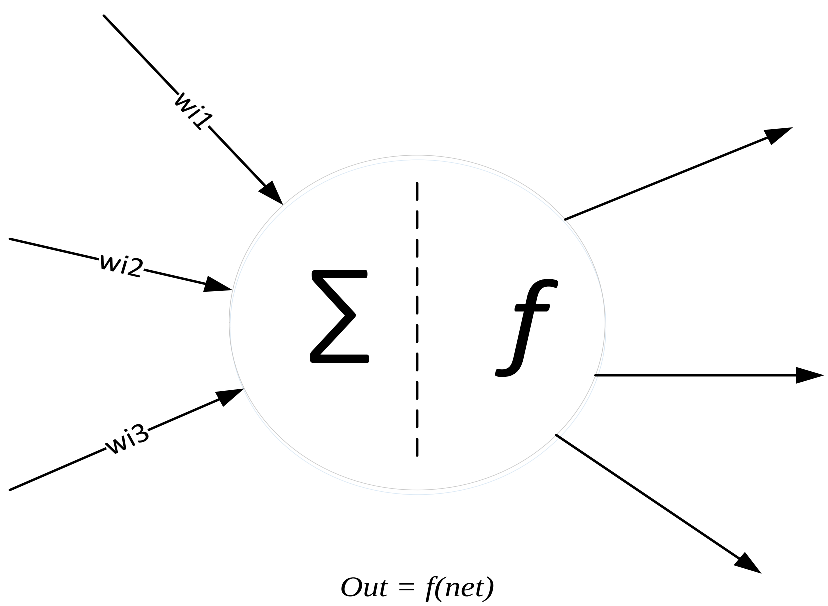


Figure 3.3: Simple structure of the neural network

The output of the node shown in the figure above can be given based on the next equation:

$$out = \sum \omega_i x_i \tag{2.2}$$

Where the x term denotes the inputs to the node and the omega denotes the associated weight to each input.

3.4.1 Components of the Neural Networks

All types of artificial neural networks have the same components regardless of the position of the neuron. The main components are explained below. These components include weights, activation functions, summation elements, and scaling elements.

3.4.2 Synaptic weights

Artificial neuron receives many coincident signals from different sources. Each one of the inputs has its own participation in the output of the system. The impact of each one of the inputs is different from the other inputs. For this reason, each input is associated with a weight or factor that manipulates the participation of the input in the summing output. Some inputs are assigned more importance than others based on the training of the neurons. The greater the weight assigned to the input, the greater the effect of the input on the result of the network. Weights are adaptive factors inside the neural net. They decide the concentration of the entering signal as recorded in the memory of the neural network. They can be considered as an evaluation of the strength of the neuron input. These weights can be adjusted as a result of multiple learning methods and dependent on the topology of the used network.

3.4.3 Layers

The layer in the neural network is a structure that contains different parts of the neural networks inside it. Any neural network must have at least two layers in it; one for receiving the inputs whiles the other is used to generate the outputs. Some structures of the neural networks have multiple layers called hidden layers. Each layer contains inside it a number of weights and summing functions.

3.4.4 Summation functions

Each structure of neural networks is constructed based on summing the inputs received at its input and send the result to the output. Simply, the summation function is the function that weights the inputs, find their sum, and send the result to another layer of structure. This process is done through the use of scalar or vector product between the inputs of the neuron and the weights of that neuron. Suppose having the inputs(x1, x2, ….xn) to a network that has n weights (w1, w2, ….wn). the output generated frolm these inputs is given by:

$$out = \sum \omega_i x_i \tag{2.3}$$

3.4.5 Activation function

The output calculated in the summing function is generally passed through another operator called transfer function. The transfer function decides the output of the neuron in term of efficiency of the input. Transfer function takes the result of the summation and produces a suitable output of it. In fact, there exit many shapes of transfer functions in artificial neural networks. Ramps, hard limits, and sigmoid transfer functions are the main types of transfer functions used in neural network applications.

3.4.6 Linear activation function

This type of activation function employs a linear ramp equation to generate the output of the function. The output of this function changes linearly with input and has no limits. This function is considered soft as it changes slowly with the output and linearly increasing or decreasing.

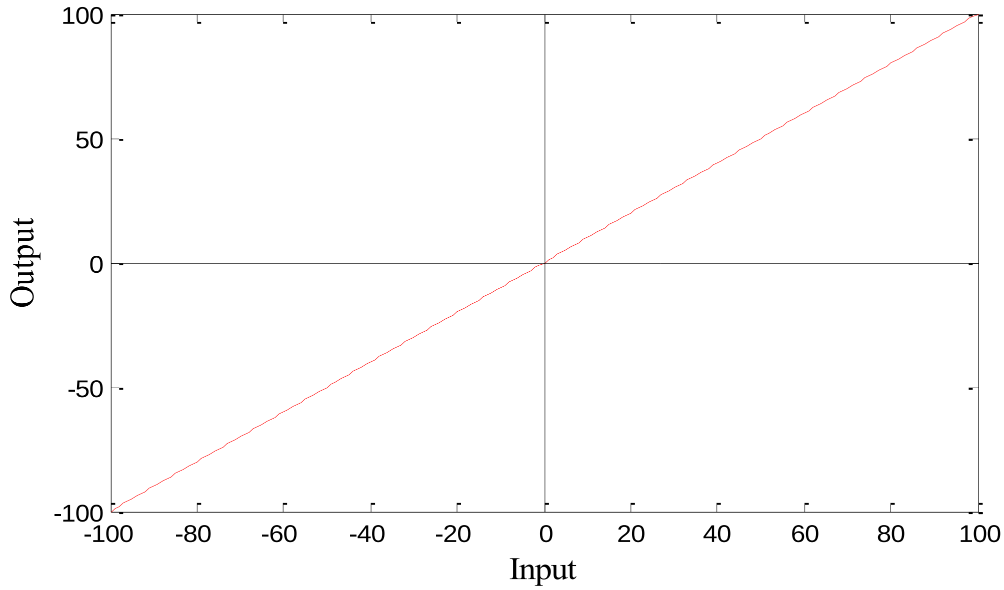


Figure 3.4: Linear activation function

Figure 3.4 presents an example of linear activation function with slope of unity. The slope can be manipulated to meet the needs of different applications. Some other type of activation functions has limits on the output that ensure the output is saturated and converges always toward a value. **Figure 3.5** illustrates the shape of a saturated linear activation function.

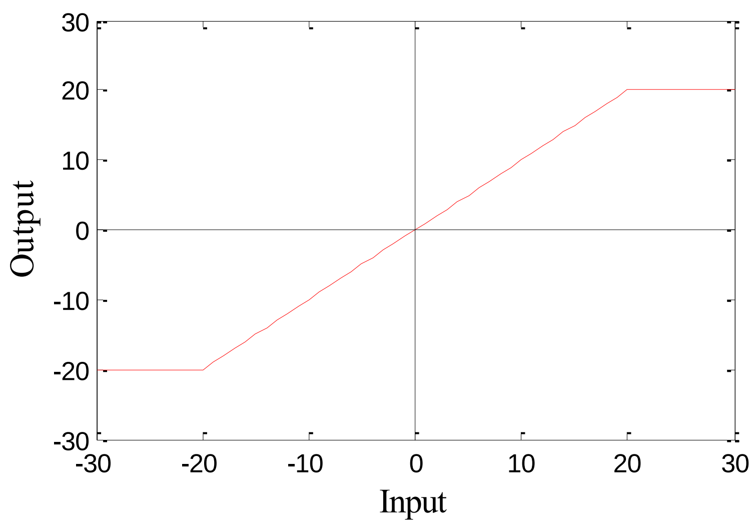


Figure 3.5: Saturated linear activation function

3.4.7 Sigmoid transfer function

Sigmoid is a mathematical function that is widely implemented in neural networks. The sigmoid function is adaptable and can change based on the parameters used with it. It can be used as linear limited function, hard limit function, or non linear function. There are two different types of the sigmoid functions. These are the logarithmic and the tangential sigmoid presented in **Figure 3.6** and **Figure 3.7** below.

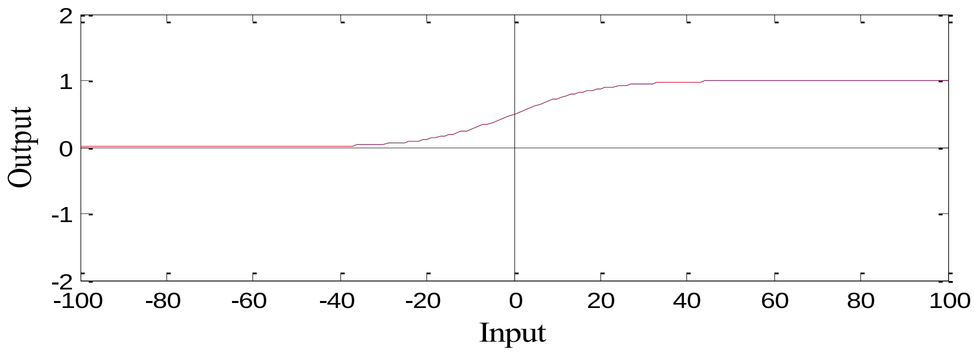


Figure 3.6: Sigmoid transfer function of ANN (logsig)

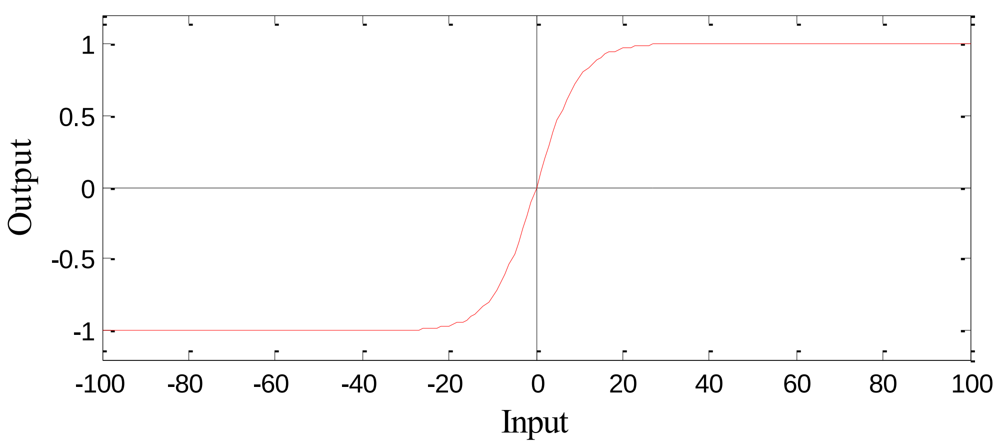


Figure 3.7: Sigmoid transfer function (tansig function)

Figure 3.8 illustrates the use of another type of transfer functions which is the radial basis transfer function. Its shape looks like a bell around the zero point. This transfer function also can be used in ANN applications.

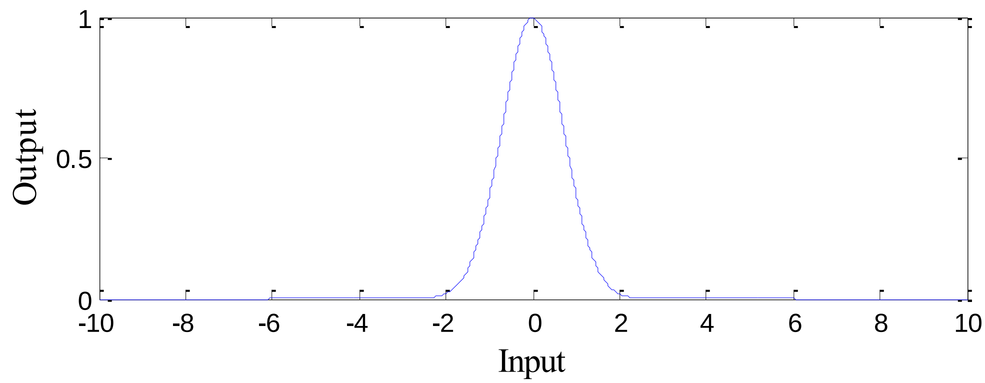


Figure 3.8: Radial basis transfer function

3.5 Types of Neural Networks

Neural networks layers are connected in between via different layers and connections. The connections are in general unidirectional connections going from the input toward the output. The input for a neuron can be single or multiple inputs. However, each neuron produces one output. Neural networks can be classified according to the types of their connection into different types.

3.5.1 Fully connected neural networks

In this type of neural network, each one of the neurons is connected to every single neuron of the next and previous layer. Such type of connection is illustrated in the **Figure 3.9**.

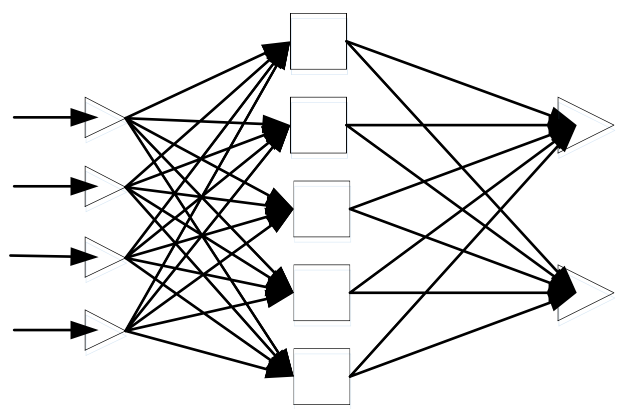


Figure 3.9: Totally connected neural network

3.5.2 Partially connected neural networks

In this topology, each neuron is not forcedly connected with all neurons in the previous and nex layer. **Figure 3.10** shows this type of connection.

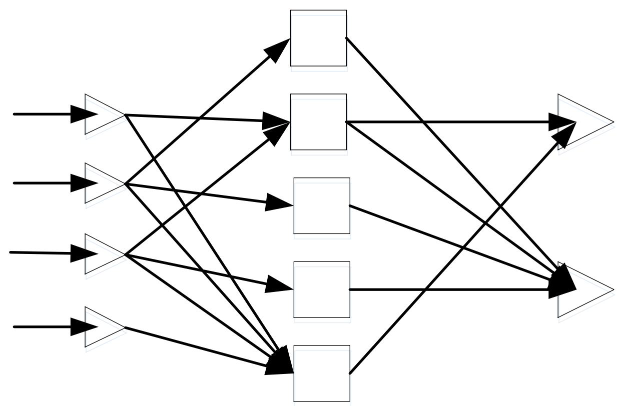


Figure 3.10: Partially connected neural networks

3.5.3 Feed Forward Neural Network

In this type of network, the signal moves in one direction from the input to the output. This type can be either fully connected or partially connected. **Figure 3.11** illustrates the connection of this type of neural network. This type is considerably implemented in different applications of the neural network. Generally, its name is connected to the back propagation learning algorithm.

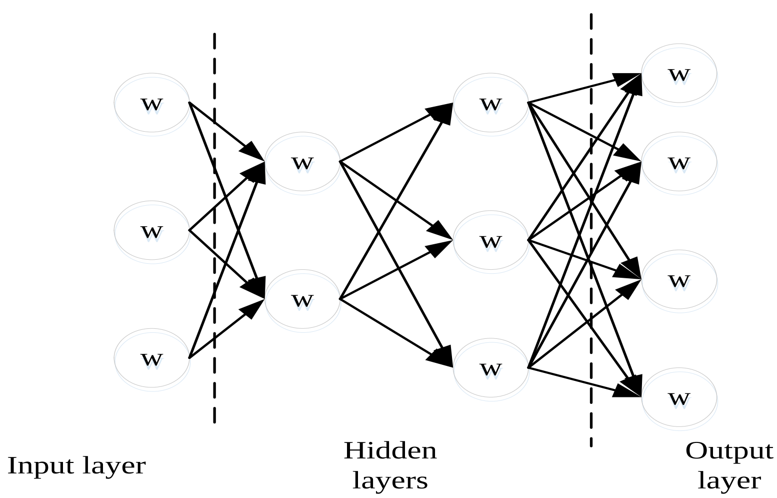


Figure 3.11: Feed forward artificial neural network structure

3.6 Back Propagation Learning Algorithm

The back propagation has been one of the most efficient types of neural networks. It is widely implemented in the training of the neural networks. Its name is derived from the fact that the error signal is back propagated toward the input layer through the different layers. The process of back propagation has two steps before being accomplished. The first step includes the forward swap over the network where all inputs are weighted and passed through layers. The generated output is then compared with a desired target to generate an error signal. The second step includes the propagation of the error signal back to the previous layer. Then back to its precedent until reaching the input layer. The weights of all layers are updated accordingly in such a way that guarantees the error minimization.

The back propagation algorithm procedure continues in a repetitive mode until the resulting error becomes small enough to generalize the network. **Figure 3.12** illustrates the idea of propagation of the error in the learning process of the network.

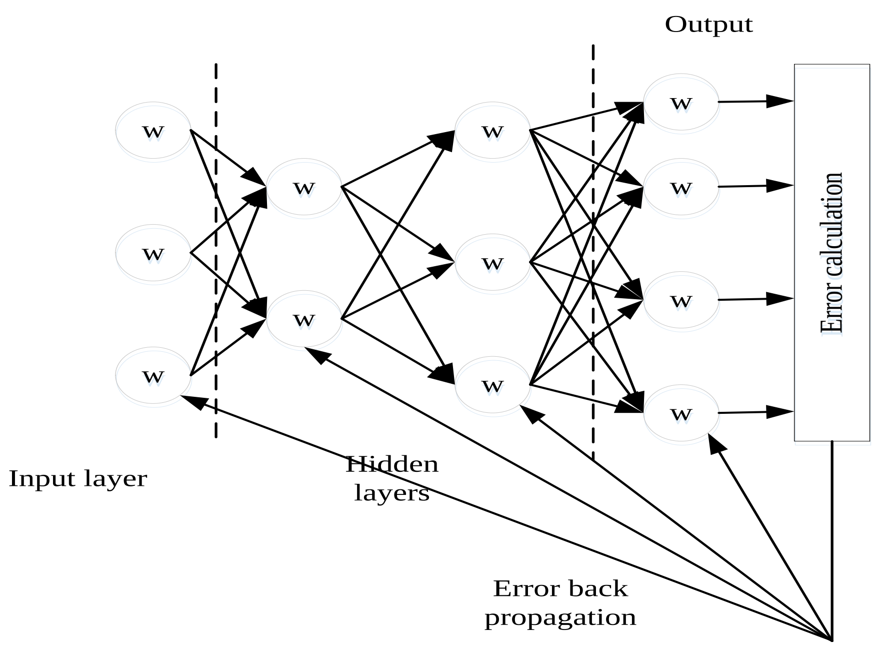


Figure 3.12: Error back propagation algorithm

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Introduction

In this chapter, the implementation of the different image processing techniques along with the back propagation artificial neural network will be presented. A new and efficient Two Step learning artificial neural network structure will also be discussed and presented in the course o this chapter. Results of the implementation will be discussed and presented.

4.2 Image Processing Techniques

In order to be able to implement the methods described in the previous chapters of this work, the flow chart of **Figure 4.1** was prepared and applied for the images of the system. The images were collected from the breast cancer database (Spanhol et al., 2016). The data base contained a huge number of images classified by experts and divided into subfolders for two different categories. These are the benign tumor and the malignant tumor categories. Each one of these categories was also subdivided into four different types of tumors. A total of eight different sub classes were obtained at the end of image classification. 560 different images for 8 different diseases were used in our implementation. The images were all treated using the same image processing techniques in order to ensure applying same effects on all the images. Samples of the processed images are presented in the next few figures.

Implementation of image processing techniques and ANN was applied using MATLAB script method. A script was written that can read all images in JPEG image format, convert them into simple gray scale image, apply median filter to the images, segment the images, compress the image size, and normalize the images. The normalized images are then

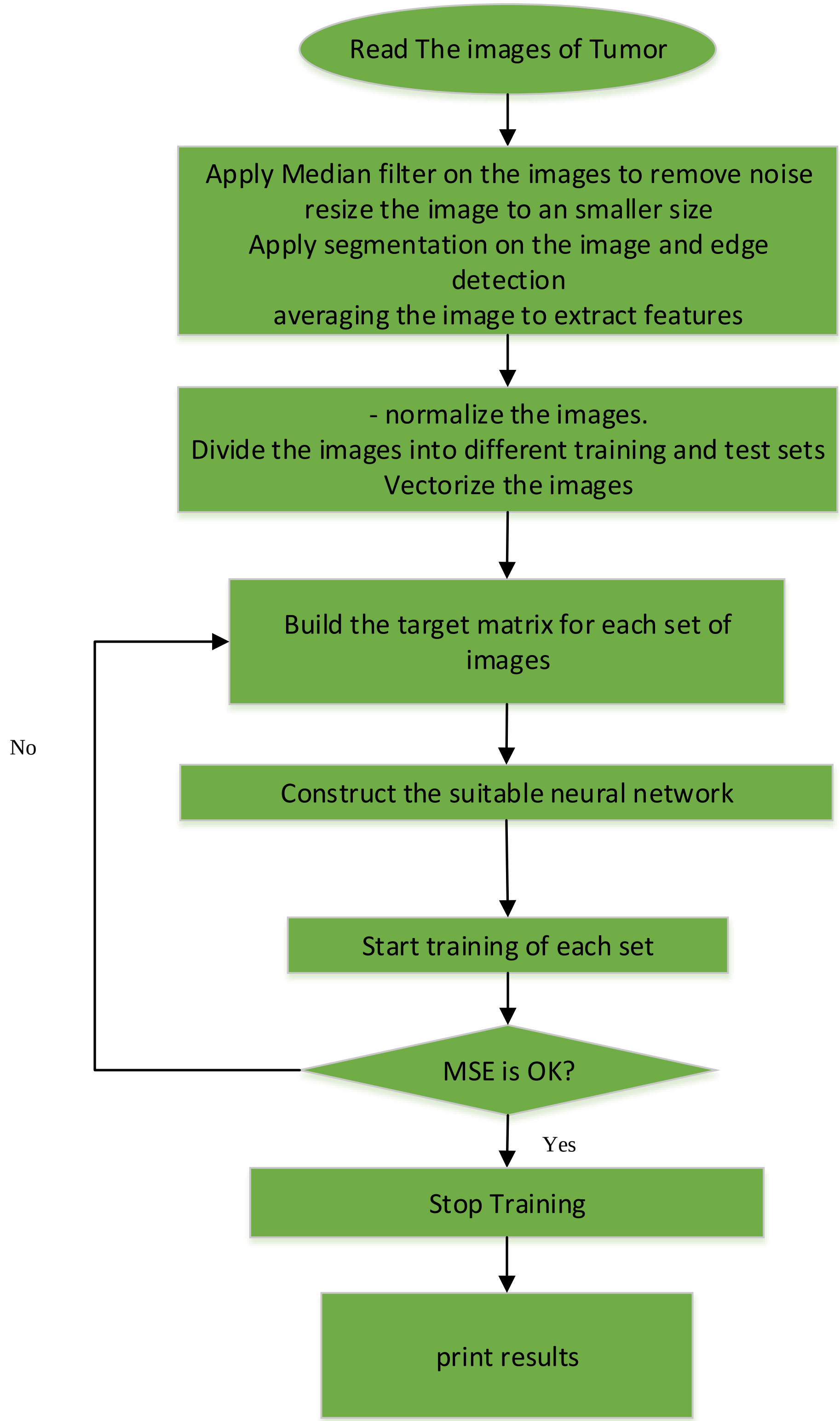


Figure 4.1: Flow chart of the proposed work

converted to one dimensional vectors that can be treated by ANN. **Figure 4.2** presents the original JPEG image before processing. The gray scale image of the original image is presented in **Figure 4.3**. **Figure 4.4** and **Figure 4.5** presents the filtered images and the size compressed images respectively.

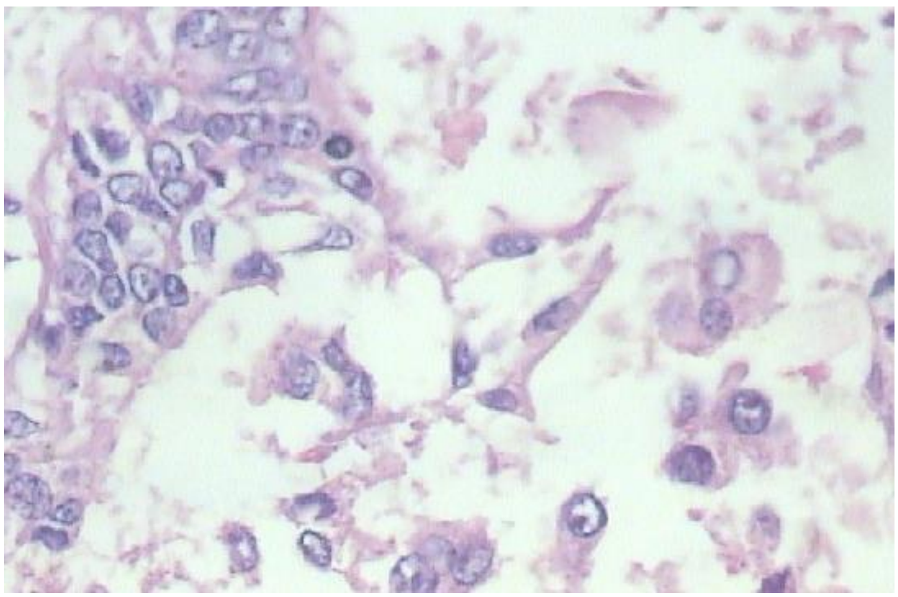


Figure 4.2: Original image of the tissue

The gray scale image shown below is, as seen from the figure containing details of the light intensity concentration of each pixel of the image with no information about the frequency distribution of the light. Its main advantage for computerized image processing resides in its small size compared to the RGB image format.

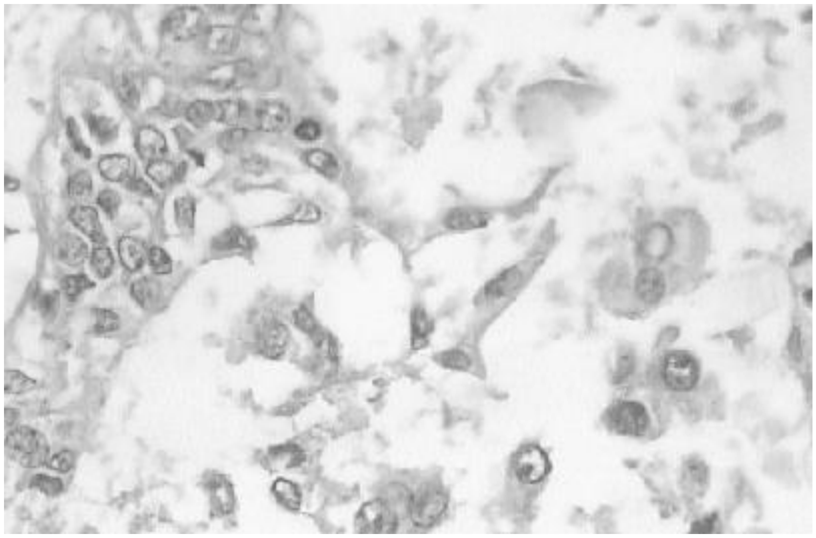


Figure 4.3: Converted gray scale image

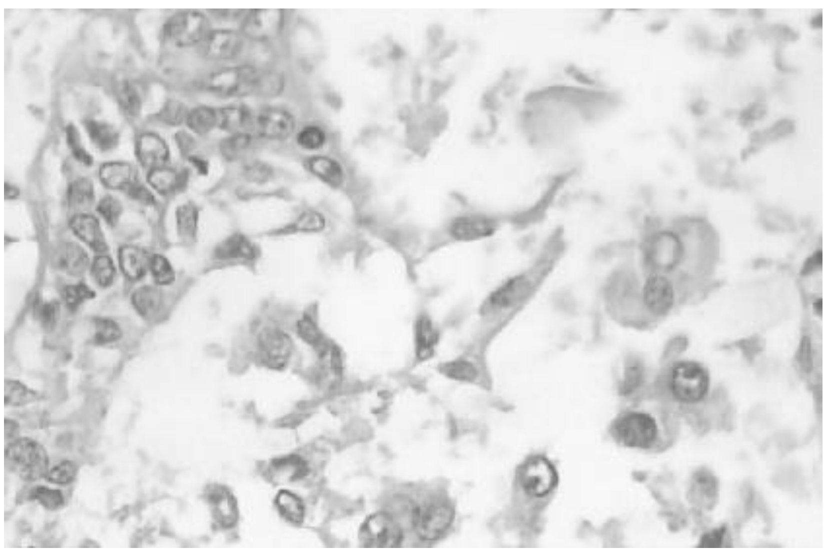
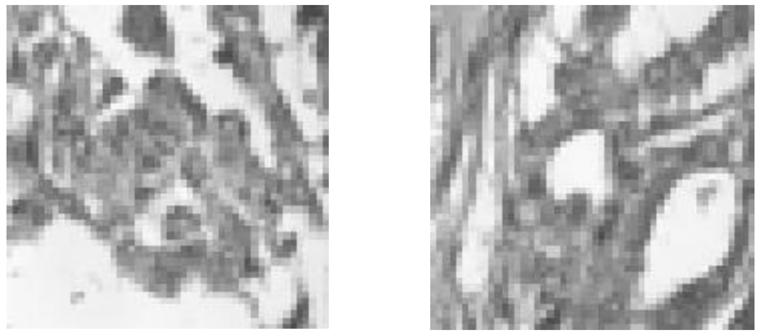


Figure 4.4: Filtered image using median filter



Resized images 50*50

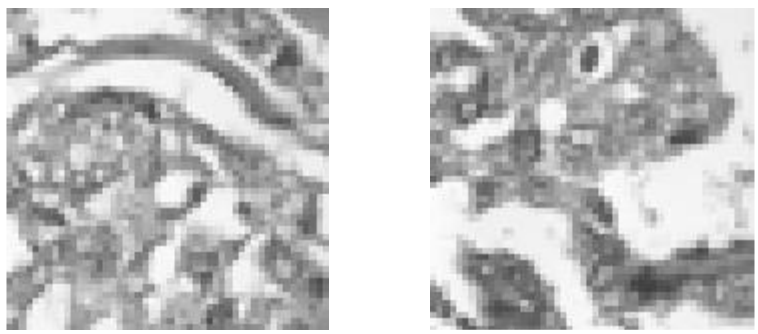


Figure 4.5: Small images fitted to ANN structure

4.3 Back Propagation Artificial Neural Network

In this part of the chapter, the application of the back propagation learning algorithm on the artificial neural network for classification of medical images will be presented. The processed images of the previous section of this chapter were presented to the neural network during the training process. The total number of 560 different images were treated and used for the training and test of the network. 160 images out of the 560 images were presented to the network during the training process. The rest of images were preserved for the purpose of testing the network. The training of the network was applied using the parameters given in the **Error! Reference source not found.**. The training was initialized with arbitrary weights given to the hidden and output layers. It took the network approximately 2 minutes and 9 seconds to converge toward the correct values of the desired output as illustrated in **Figure 4.7**. **Figure 4.7** presents also the curve of the MSE evolution as function of the training time. It is clear that the MSE was decreasing all the time with the training evolution.

Table 4.1: Back propagation training parameters

Parameter	Value	Parameter	Value
Network type	Back propagation	Learning rate	0.0002
Network size	3 layers	Momentum value	0.01
Input layer	2500	MSE	$9.58 * 10^{-5}$
Hidden layer/s	600	Time (s)	129
Output layer	8	Epochs	325
Transfer function/s	Tangent sigmoid	Training efficiency	97.5%
Test efficiency	85.5	Total efficiency	89%

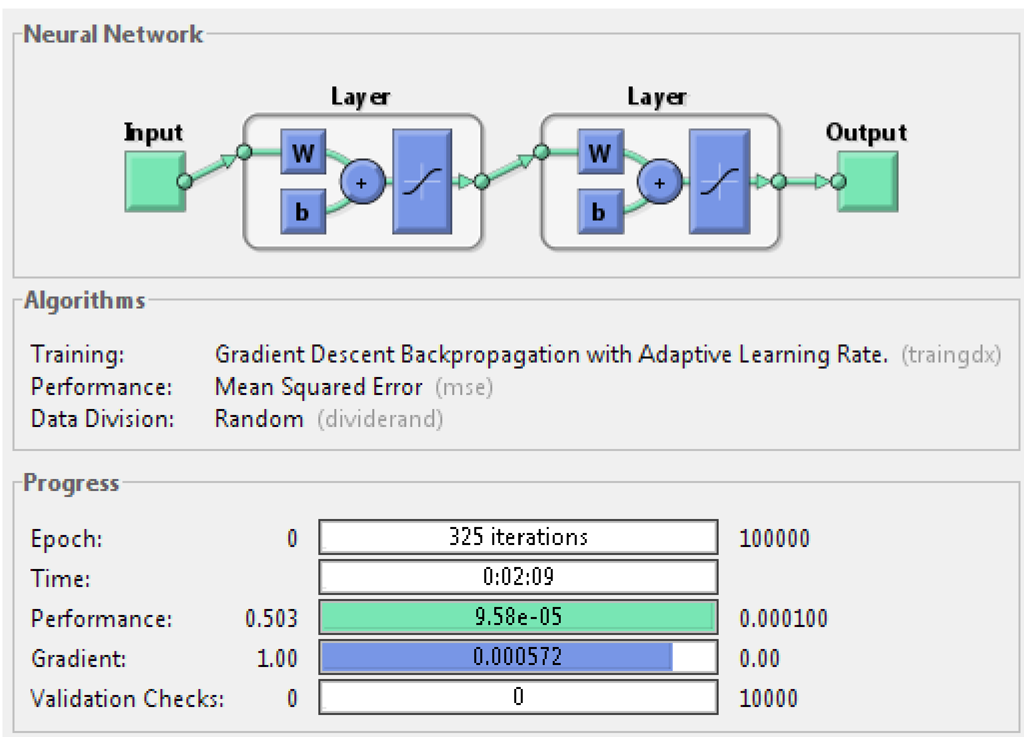


Figure 4.6: Training tool of the artificial neural network

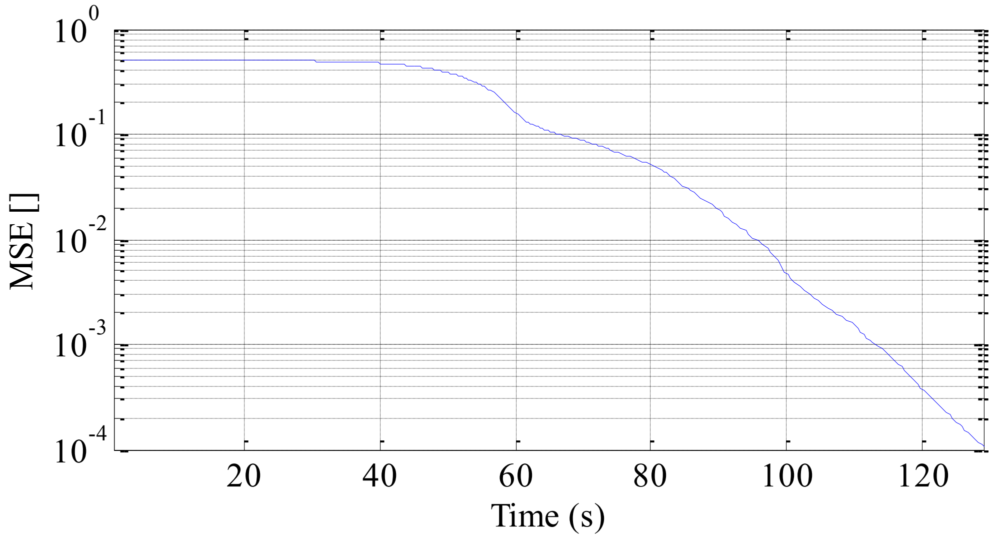


Figure 4.7: Training MSE evolution with time

Figure 4.6 presents the ANN training tool of MATLAN where the structure of network, layers, MSE, iterations and much other information are available. The training of the system has shown a high training efficiency of 100% with 160 recognized images out of 160 total training images. **Table 4.2** presents the obtained output of the first sample of training images as generated by the neural trained networks. It is obvious that all 8 diseases were recognized correctly with high accuracy. The outputs generated from the network are similar to the desired targets specified by the user in the beginning of the training process.

Table 4.2: Training output of first sample of images

D1	D2	D3	D4	D5	D6	D7	D8
0,932	0,018	0,007	0,010	0,007	0,004	0,005	0,004
0,021	0,575	0,016	0,001	0,008	0,010	0,001	0,002
0,087	0,116	0,978	0,015	0,009	0,004	0,014	0,004
0,001	0,002	0,008	0,979	0,005	0,003	0,003	0,011
0,003	0,028	0,003	0,009	0,981	0,033	0,022	0,004
0,091	0,001	0,002	0,004	0,010	0,936	0,001	0,010
0,001	0,018	0,000	0,002	0,003	0,001	0,774	0,010
0,000	0,006	0,002	0,003	0,007	0,012	0,022	0,984

Table 4.3 presents the output of the first test set of images after the generalization of the network. The eight different diseases were recognized correctly with good approximation. It is

to mention here that a threshold of 0.5 was accepted in our work for both training and test outputs.

Table 4.3: Test output of first sample of images

D1	D2	D3	D4	D5	D6	D7	D8
0,932	0,018	0,007	0,010	0,007	0,004	0,005	0,004
0,021	0,575	0,016	0,001	0,008	0,010	0,001	0,002
0,087	0,316	0,978	0,015	0,009	0,004	0,014	0,004
0,001	0,002	0,008	0,979	0,005	0,003	0,003	0,011
0,003	0,028	0,003	0,009	0,981	0,033	0,022	0,004
0,091	0,001	0,002	0,004	0,010	0,936	0,001	0,010
0,001	0,018	0,000	0,002	0,003	0,001	0,774	0,010
0,000	0,006	0,002	0,003	0,007	0,012	0,022	0,984

To evaluate the performance of the back propagation network under different parameters, another experiment based on the parameters given in the **Table 4.4** was carried out. The same number of training and test images was used in this experiment. 160 training images against 400 test images were implemented. A training efficiency of 96.3% was obtained after 1 minute of training of the network. The test efficiency of 80% was obtained. 6 incorrect predictions were found in the training set of this structure. Samples of the training and test outputs of this training set are presented in **Table 4.5** and **Table 4.6**.where the red column signify an incorrect answer.

Table 4.4: Parameters of the second ANN experiment

Parameter	**Value**	**Parameter**	**Value**
Network type	Back propagation	Learning rate	0.2
Network size	4 layers (2 hidden)	Momentum value	0.1
Input layer	2500	MSE	$9.87 * 10^{-5}$
Hidden layer/s	800, 250	Time (s)	62
Output layer	8	Epochs	130
Transfer function/s	Tangent sigmoid	Training efficiency	96.3%
Test efficiency	80%	system efficiency	85%

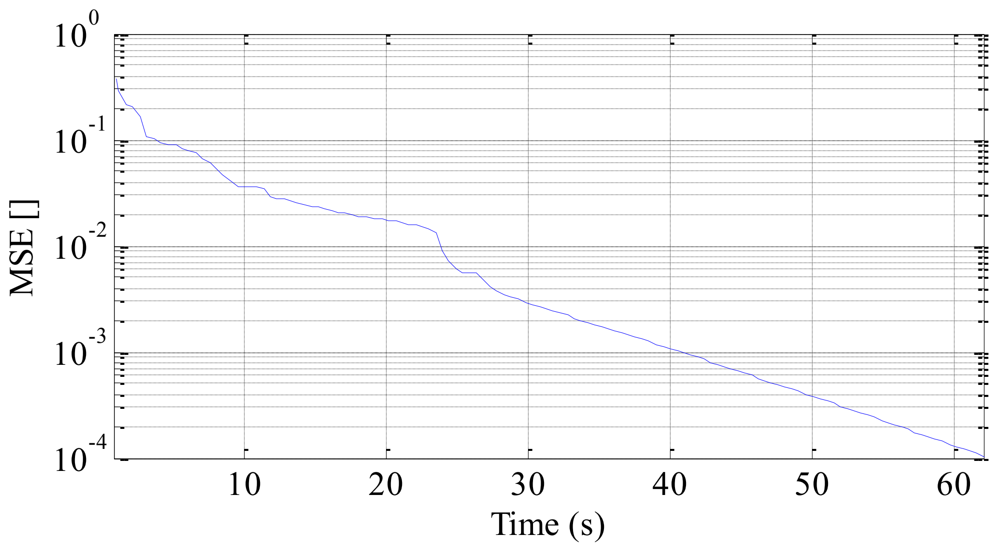


Figure 4.8: Curve of MSE during the training

Table 4.5: Training output of sample images

D1	D2	D3	D4	D5	D6	D7	D8
0,986	0,010	0,007	0,012	0,001	0,001	0,000	0,001
0,015	0,981	0,016	0,007	0,002	0,028	0,004	0,001
0,013	0,014	0,983	0,014	0,004	0,002	0,003	0,002
0,002	0,003	0,013	0,979	0,010	0,001	0,001	0,016
0,005	0,004	0,001	0,013	0,982	0,007	0,011	0,013
0,007	0,007	0,002	0,002	0,002	0,891	0,009	0,005
0,001	0,006	0,000	0,001	0,009	0,005	0,982	0,051
0,002	0,001	0,004	0,002	0,002	0,009	0,013	0,607

Table 4.6: Test output of sample of images

D1	D2	D3	D4	D5	D6	D7	D8
0,986	0,010	0,007	0,012	0,001	0,001	0,000	0,001
0,015	0,981	0,016	0,007	0,002	0,028	0,004	0,001
0,013	0,014	0,983	0,014	0,004	0,002	0,003	0,002
0,002	0,003	0,013	0,979	0,010	0,001	0,001	0,016
0,005	0,004	0,001	0,013	0,982	0,007	0,011	0,013
0,007	0,007	0,002	0,002	0,002	0,891	0,009	0,005
0,001	0,006	0,000	0,001	0,009	0,005	0,982	0,513
0,002	0,001	0,004	0,002	0,002	0,009	0,013	0,131

Figure 4.8 above presents the MSE evolution curve during the training time that shows a decreasing line until it reaches the pre-set value of 0.00001.

4.4 Two Step Learning Artificial Neural Network

The Two Step learning artificial neural network training algorithm was applied on the dataset. Two step learning is used to increase the efficiency of the neural network in classification and recognition. Instead of using the network in one stage of training, two successive training stages are implemented in this learning process. The first stage is used to extract features of images and store them in the weights of the hidden layer. It is normally short and takes less than 100 epochs. The inputs and outputs of this stage are same. The obtained weights of this stage are then used in the training of the second stage. This reduces the training time, processing cost, and increases the efficiency of the learned network. **Table 4.7** resumes the parameters of the used Two Step learning process in this experiment. It is noticed that the two stages were constructed of 100 hidden neurons instead of 600 in the normal Back propagation ANN. The training time was also less than that of BPANN. The efficiency of this method was 98.4% in total. Total of 294 epochs were required to obtain a minimal MSE of $2*10^{-7}$.

Table 4.7: Parameters of the two step learning ANN

Parameter	Value	Parameter	Value
Network type	Two step learning	Learning rate	0.3
Learning stages	2	Hidden 1	100
Network size	3 layers	Momentum value	0.6
Input layer	2500	MSE	$2.2 * 10^{-7}$
Hidden layer/s	100	Time (s)	31, 23
Output layer	8	Epochs	100,194
Transfer function/s	logarithmic sigmoid	Training efficiency	100%
Test efficiency	97.8%	system efficiency	98.4%

Figure 4.9 and **Figure 4.10** present the MSE curves during the training of the two stage of the neural network. It is seen that the MSE curve was decreasing during both stages.

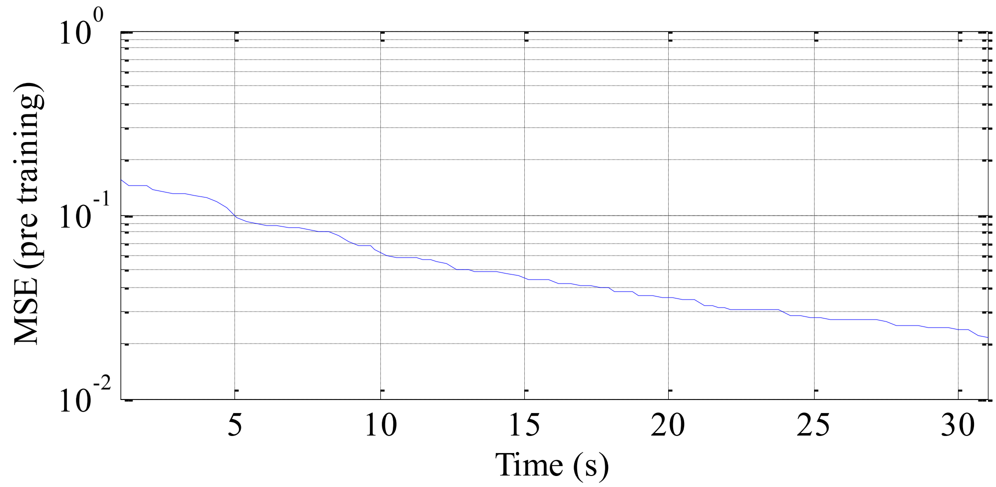


Figure 4.9: MSE curve of the pre-training network

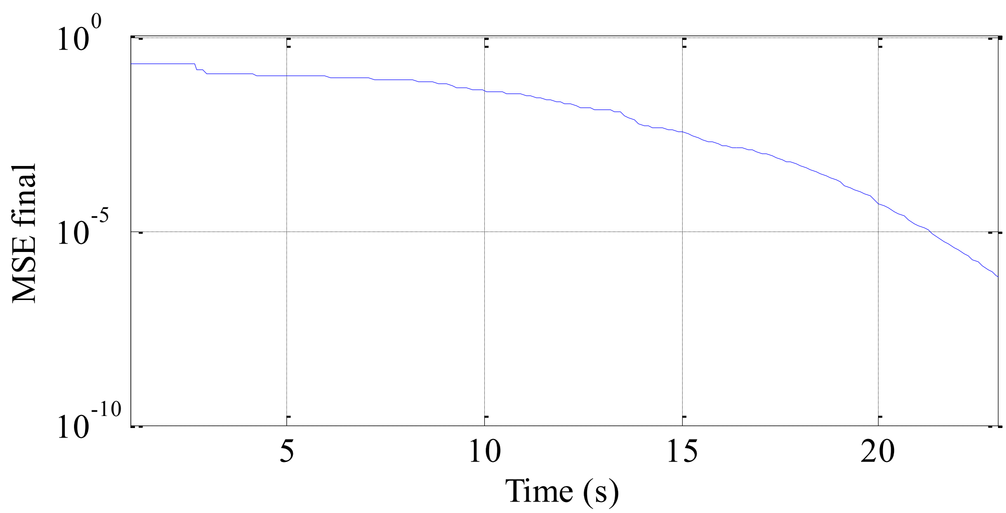


Figure 4.10: MSE curve of the fine tuning stage of Two step ANN

4.5 Back Propagation ANN without Median Filter

In this part of the work, the back propagation algorithm was applied on the training images without Applying Median filter on the images. Different ANN parameters and layer neurons were applied in this experiment. The results of the experiment were all collected and resumed in the table 4.8 below.

Table 4.8: Comparison of back propagation algorithm results

No	Hidden neurons	Moment. factor	Learning rate	Training result	Test result
1	600	0.05	0.002	95%	81%
2	600	0.2	0.01	96%	83%
3	600	0.2	0.1	92%	78%
4	600	0.05	0.01	97%	80%
5	800	0.05	0.01	94%	82%
6	1000	0.05	0.01	90%	75%
7	500	0.05	0.01	91%	78%
8	300	0.05	0.01	92%	81%

From the table above, it is noticed that changing the parameters of the neural network can affect the obtained results of the training. The removal of Median filter also can affect the results with less effect because the images noise is very low. Median filter can be seen very important in the case where some noise is existent in the images.

CHAPTER 5

CONCLUSIONS

In this work, the implementation of artificial neural network structures for the detection of breast cancer was implemented. The use of back propagation neural network and two step learning based neural network was presented and discussed. Breast cancer is one of the mortal types of cancer if not treated in its early stages. 12.6% of the world's women are possible subjects to this disease according to different medical reports. Researches on the breast cancer show that the early treatment of the disease is very important to save lives of millions of women. However, the early detection of the disease using classic methods and periodic tests is less effective due to the lack of specialized medical centres in many areas around the world. The use of simple specialized technologies becomes indispensable in this case. This work presented the use of artificial neural networks for the early detection of the breast cancer. The proposed work implements two different types of neural networks in its function. These are the back propagation neural network and the two step learning neural network. Images of infected and healthy tissue of the women breasts were used in the presented work. Those images were all collected from trusted medical sources and institutes. All the database images were classified by qualified medical experts into two groups. The first group represents healthy tissues with no signs of any malignant infections or tumors. The other group is infected by malignant type of cancer. The two groups were also subdivided into 8 different types of tumors. Total of 560 images were used in this work and divided into eight types of tumors. Four types of tumors were classified as malignant tumors while the other four types were classified as benign tumors. All database images were treated equally using same image processing techniques to assist the function of the neural networks. Median filter and image segmentation methods were applied to filter the images and to extract the important features from them.

Back propagation algorithm was implemented using 1 and 2 hidden layers in the network. The use of one hidden layer has given high speed training of the network in 129 seconds with an overall system efficiency of 89%. The test efficiency of the system was approximately 85.5%. The use of two hidden layers with back propagation algorithm has given faster convergence for the system in 62 seconds however the efficiency was reduced to 85% instead of 89%. The implementation of two step learning neural network has improved the results to 98% as an average during a training time of 31 seconds.

The obtained results in this work show that the two step learning neural network is more efficient in the detection of the cancer and its classification. It is more efficient in term of classification accuracy and time response of the system.

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