APPEARANCE BASED GAZE ESTIMATION SUING NEURAL NETWORK

BRAIN TUMOR DETECTION AND CLASSIFICATION USING NEURAL NETWORK

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

By ABDULHAMID AL-ANTOUT

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.

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I am very happy for the time am here finishing two years of my master study and preparing for the presentation of my master thesis. On this occasion, I would be happy to thank my beloved supervisor Assist. Prof. Dr. Kamil DIMILILER; for all his patience and helpful advices without which I wouldn't be at this point today. I owe him a lot of my success at this day and I can't pay for his efforts. I would also like to thank the members of my family, my friends, and all the Libyan students in TRNC.

To my parents and family....

ABSTRACT

Brain tumor or cancer is one of the most dangerous types of cancers as it affects the main nervous system of the human body. The brain is very sensitive to the infections that can affect its functions. Brain cells are sensitive and difficult to be renewed if been infected by dangerous diseases. There are two different types of brain tumors. It can be classified into benign and malignant tumors. The benign tumor is a change in the shape and structure of the cells that needs to be treated but can't infect the other cells or spread in the other parts of the brain. The malignant tumor is very dangerous and can spread and grow if not treated with care and removed directly. The detection of brain tumors is a complicated and sensitive task that implied the experience of the classifier. The use of ANN system to classify the brain tumor type is presented in this work. ANN can resume the experience of experts and implement it in one computer based structure. This can reduce the cost and increase the performance of brain tumor detection. Back propagation algorithm is proposed in this work for the classification of brain tumors.

Keywords: Artificial networks; back propagation; brain tumor; image processing; malignant tumor

ÖZET

Beyin tümörü veya kanser, insan vücudunun sinir sistemini etkileyen en tehlikeli kanser türlerinden biridir. Beyin, fonksiyonlarını olumsuz etkileyen infeksiyonlara karşı çok hassastır. Beyin hücreleri hassastırlar ve de tehlikeli hastalıkları durumunda yenilenmeleri çok zordur. İki tür beyin tümörü vardır. Kötü huylu ve iyi huylu diye sınıflandırılabilirler. İyi huylu tümörde beyin hücrelerinde şekil ve yapı de eğişikliği görülür ve bunlar diğer hücreleri etkilemez ve beyinde yayılmaz. Kötü huylu tümör ise çok tehlikelidir ve eğer dikkatli tedavisi yapılmaz veya tamamen alınmazsa yayılıp büyüyebilir. Beyin tümörlerinin teşhisi karmaşık ve hassas bir işlemdir. Tecrübeler de bunu göstermektedir. Beyin tümörü sınıflandırılmasında kullanılan Yapay Sinir Ağlar sistemi bu çalışmada ele alnmıştır. Yapay Sinir Ağları uzmanların bu konuda deneyimlere başlamasına ve bu olguyu bilgisayar ortamina koyabilmelerine öncülük edebilir. Bu uygulama hem giderlerin düşmesine hem de tümör teşhisinde perrformansı artırabnilir. Bu çalvmada, beyin tümörlerinin sinfflandirilmasi için geri yayinimli algoritmai teklif edilmektedir.

Anahtar kelimeler: Yapay ağlar; geri yayılım; beyin tumour; sanal yazılım; kötü huylu

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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

Brain tumor is one of the most mortal types of cancer infections. It has its high effects because it is very clause to the main neuronal motor of the human being where every small defect can cost a lot. For this reason, it is important to find methods of early detecting or alarming the possibility of the existence of brain tumor. This importance comes from the fact that early detection increases significantly the possibility of curing the disease and saving the life of patients. Recently, the treatments of cancer have greatly developed especially in the early stages of infection. Survival possibilities are very high for those patients receiving early treatments compared to those people who don't have this chance in the early stages of sickness.

Brain tumor is a mass or accumulation of biological cells in the brain. These cells are classified as abnormal cells that differ from the cure brain cells. These cells grow and increase in size inside the rigid skull that encloses the brain. This growth of the cells mass inside the hard structure of the skull forces the brain cells and causes serious pains and problems. Generally, tumors of the brain or any tumor can be classified into two types of tumor. The first is called benign tumor or non cancerous tumor; whereas the second is very dangerous and cancerous that is said to be malignant tumor. The growth of these two types of tumor inside the skull forces the brain and can be very harmful for life of patient.

Based on the origin of tumor, tumors can also be classified into two categories. These are the primary and secondary tumor. Primary tumor is originated in the brain and generally it is benign tumor type. Secondary tumor or also called metastatic is originated in other body organs like lungs and spread into brain through blood or lymph.

The early detection of any type of disease is a key stone in the cure of patient that increases the survival possibilities. This is also true in the case of brain tumor. The early detection reduces the danger on the life of patients and increases their hopes of being cured to 90%. However, early detection of the tumor is a process that involves the intervention of expert people in all evaluation process of the patient. This is costly and nearly impossible to be achieved for huge number of people. The thing that increases the importance of the use of computer aided detection of brain tumor. The CAD is a process in which the first stage of tumor detection can be achieved automatically using specialized software. The Magnetic Resonance imaging system generates the brain images while the software will be responsible to detect any different sections or areas in the brain like tumor. The CAD will then assist the human expert in generating first report of tumor possibilities. Computer based detection can play a very significant rule in the detection of brain cancer (Amsaveni, Singh, & Dheeba, 2012).

Recently, huge amount of researches were pointed toward the study of automatic tumor detection for different types of tumor (Dahab, Ghoniemy, & Selim, 2012). Researchers are encouraged to find new methods to increase the efficiency of automatic tumor detection and segmentation of MR images.

Artificial neural networks have penetrated deeply the field of image processing and medical imaging. They have become one of the main structures used in the processing of medical images and disease detection. Artificial neural networks have shown a great performance in performing tasks that are considered very complex and needs biological brain to be performed. The efficiency of ANN structures has managed them to play an important role in different medical fields. With the continuous development is digital electronics and ANN software, the artificial intelligence of neural networks is expected to become the most important early detection methods of cancerous tumor masses.

This work is focused on the study of brain tumor and its early detection based on image processing techniques and artificial neural networks. It will be concerned by the study of different brain tumor images and their processing, segmentation, and classification into benign or malignant tumors.

1.2 Literature Review

The study of cancerous tumor has attracted the attention of many researchers around the world. Hundreds of researches are being published yearly that discuss issues related to the brain tumor and the different methods for its early detection. Some of these researches rely on the use of image processing techniques like segmentation in their proposed works. Others use artificial intelligence structure to perform such tasks. In other types of researches, a combination of different detection methods is being implemented to perform the detection. In (Amsaveni et al., 2012), a classification approach was presented that is based on cascaded correlation artificial neural network. The presented method is used for classification of magnetic resonance images of brain tumor. The images region of interest was processed to extract Gabor features. The classifier was considered to be high efficient compared to other literature classifiers. Murugesan & Sukanesh, (2009) has presented their work about the use of artificial neural networks in the detection of brain tumor based on electroencephalograms. The electroencephalogram is mentioned as an efficient measure of brain activity. Feed forward back propagation algorithm was used in the training of the system and generation of the results. Segmentation of MRI brain tumor images based on clustering techniques and fuzzy logic with optimization techniques was proposed in (Gopal & Karnan, 2010). Genetic algorithms and particle swarm optimization algorithm were implemented in this work. Preprocessing and image enhancement of MR images was applied in the first stage of the work. The next step included the segmentation and classification of these MR images.

Modified image segmentation techniques were proposed and implemented on the MR brain images used to detect brain tumor in (Dahab et al., 2012). Modified probabilistic neural network technique was implemented in this work. The proposed technique was claimed to decrease the processing time to approximately 79%. Training result of 100% was also obtained in this research. Discrete cosine transform based brain tumor classification was presented by (Sridhar & Krishna, 2013). Authors also presented a neural network based brain tumor classification and presented a comparison between results. The tumor detection based on radial basis neural networks and regression based neural networks was presented in (Thara & Jasmine, 2016). The use of different types of ANN based tumor detection techniques were also presented in (Subashini & Sahoo, 2012), (Amsaveni & Singh, 2013). Unsupervised

artificial neural network for brain tumor detection was also proposed by (S. Goswami & Bhaiya, 2013). Many other researchers have also focused and studied the brain tumor detection based on different approaches and new techniques.

1.3 Problem of the Study

The problem of the study is the early detection of the brain tumor for efficient cure of the patients. Late detection of tumor and brain tumor in particular is the cause of the death of a huge number of patients. The early detection and classification of brain tumor will increase the chances to treat and cure patients.

1.4 Methodology of the Work

In order to achieve the goals of this work and to meet the requirements needed to share in solving the proposed problem; this work will be arranged in the order that offers the best results and will be fitted within the limits of the thesis possibilities. First of all, the data collection of different brain magnetic resonance images will be carried out. For the reason of lack of database resources for brain tumor images; database from different sources will be combined and treated. The collected database will then be processed and treated before the classification process is started. The images will also be segmented and then fed to the neural network to be classified.

1.5 Contribution in the Field of Study

The work will be considered as a contribution in the field of cancer early detection efforts in general. It studies the literature of the topic and tries to give a hand on the main results obtained. In the next stage, the program will apply the proposed method of ANN to check the capability for disease detection and compare with literature. Different image processing steps can offer different results and thus may ameliorate considerably the output efficiency. For this reason, combination of image processing techniques including enhancement and segmentation will be presented. All results will be compared with literature upon the end of the work. Future works will be discussed based on the obtained results.

1.6 Database Used in This Work

The database of the study is constructed of two types of brain MR images. These are the mining tumor images and the malignant tumor or cure images. In our database there is total of 174 brain MR images. 118 of these images are benign images while the rest of images represent malignant tumor images. Figure below shows a sample of the presented images.



(a) Malignant tumor





Figure 1.1: Sample of the used database of brain MRI

1.7 Flowchart of the Work

The work will start initially by collecting and separating the database into benign and malignant brain tumor. The whole data will then pass through the image processing step. In the image processing, all images will be first read as 'RGB' form and converted to gray scale images. The gray scale images will then be enhanced using filters (Weiner filter initially is going to be used as it offers better performance). Images will then be segmented by conversion to binary and thre-sholding of the image. Wavelet transform will be applied on the image to extract main features. The image is then normalized to be suited for use with neural network structure. upon the end of image processing step, the neural network is then started. The structure that will be used is the multilayer neural network based on back propagation algorithm. All normalized images will be fed to the network to be trained to classify different images. The flowchart of this work is presented in the next form. The flowchart is composed of two parts; the left part concerns the image processing part. The processed images will be

transmitted to the ANN part of the right. Image processing includes RGB to Gray conversion, filtering, image enhancement, segmentation, and Wavelet transform.



Figure 1.2: Flowchart of the proposed work

CHAPTER 2

ARTIFICIAL NEURAL NETWORKS

2.1 Introduction

Neural networks are very rapid and precise due to the fact that the completion of training the processing, optimization and time consuming calculations are no more needed. The generation of outputs of the network is straight forward from the provided inputs. The network is constructed by teaching the network how the specific system behaves with each one of the inputs. There exist different network types implemented for different applications. Neural networks are used in engineering, forecasting of weather and financial markets, oil prices forecasting, business, and medical fields. They have the power and capability to generalize different problems (Coit, Jackson, & Smith, 1998).

In general, artificial neural applications can be divided into categories of data clustering, and data arrangement. Data clustering is the process of finding relationships between different data inputs and arranging them into categories based on common features between them. In the classification applications, different inputs are assigned to defined classes to which they belong. In the regression, a curve is created such that it can be considered as the best fit between training sets. The most common regression neural networks are feed forward networks and recurrent neural networks. The neural network architecture and main types of ANN will be discussed in this chapter of the work. Different variables that can affect the function of ANN and used as parameters will be discussed as well.

The human mind is the main decision motor in the human being. It consists of billions of nerves that are interconnected in a very complex structure. The brain as we can imagine its structure is faster and more powerful than any computer that was manufactured. It can easily handle complicated problems with minimum effort and in parallel manner that can't be handled by any computer. The biological analysis of the brain shows that it has multiple sets of layers of neurons connected between each other to perform parallel processing tasks. The parallel processing is very important for fast and accurate processing of data of information

like images. the human brain is very fantastic in recognizing and memorizing images of things and humans with the minimum effort and processing time. Each one of the neurons in the brain is connected to millions of other neurons to interchange the data in the best manner. Each neuron receives and sends information to all surrounding neurons.

The biological neuron shown in the **Figure 2.1** consists of different parts that help it to complete its function. Main parts of the biological neuron are cell body (Soma), Dendrites, Synapses weights, and axon. Each on e of the billions of biological cells is connected with all surrounding neurons. The axon is the output of the neuron through which it can transmit the information to the next neurons.



Figure 2.1: Biological neuron structure

The brain has strong decision making characteristics that help it to solve very complex problems such as motion detection and recognition, mathematical problems, and others. This ability is obtained and ameliorated by stocking all previous experiences and generalizing them to similar problems. Scientists tried to mimic the function and structure of the brain into the computer to create the artificial networks. This artificial network uses the training and learning in similar way of the brain. ANN is an intelligent mathematical algorithm that consists of three main parts (A.D.Dongare, R.R.Kharde, & D.Kachare, 2012):

- (1) input layer,
- (2) middle or hidden layers
- (3) output layer.

2.2 Input Layer

The input layer is considered the input of the neural network that can receive any signal and transmits it to the next processing layer. Generally, input layer is known as a non processing layer as the information is transmitted without any modifications. It is simply a vector that handles the inputs of the network preparing to send them to the hidden layers.

2.3 Hidden Layers

Hidden layers in the neural network are of very great importance as they hold most of the processing operations of the neural network. They affect very strongly the function of the neural network and can affect the performance of the network. It is the core of the ANN and consists of many smaller units known by neurons. The main mathematical calculations are applied and carried out inside the neuron unit. They all process the different inputs and provide the different outputs. Each neuron in the hidden layers is responsible to receive and send information from the other neurons (A.D.Dongare et al., 2012). The received and sent information from and to a specific neuron is processed differently based on different categories such as the weight of the neuron and its position.

2.4 Output Layer

Output layer is the last layer that generates the output of the whole network based on the processed information. It has a very important rule during the training of the network as it is the laboratory in which the generated data is checked and compared with the desired outputs. Different methods are used to generate the error in the output layer preparing to send them back to the previous neurons during the learning process.



Figure 2.2: Structure of the neural network

The Figure 2.2 above represents the main structure of artificial neural network. The first level presents the input layer were inputs are being received to the neural network. The second level shows the hidden layer, while the third level shows the output y of the neural network. The weights in the neural network

The neural networks are a type of optimization functions that use the weight values as design values. These values are to be found and adjusted correctly to obtain the desired result. This optimisation function utilises the mean squared error MSE approach as a minimisation function. The MSE is the difference between the expected results of the network and the exact results. The general optimisation formula in ANN is given by:

find
$$W_i^j \in \Re$$

to min imize : $MSE = \sum_{i}^{N} (Y_i - T_i)^2$ (2.1)

There are different structures and algorithms for the neural networks. Different models of the network and learning algorithms were presented and studied. The basic model of the neural network is the network with one input and one output network. More complicated structures of

multiple layers, inputs, and outputs are also existent. The complexity of the network is in general a function of the solved problem. Some problems are simple and easy to be solved; they don't need multilayer structures or multiple input output combinations.

2.5 Structure of the Artificial Neuron

As we said earlier, the neural network consists of multiple simple neurons. The neuron is constructed as shown in the Figure 2.3. Different inputs of the neuron are being collected and fed to the body of the neuron. These inputs are summed together and then fed to an activation function to generate the suitable output. The dynamics of the signal can be modelled as discrete or continuous. The transfer or activation function decides whether to generate an output or deactivate it. Some transfer functions generate proportional signals with their inputs. The summation function is given by:

$$O_j = \sum_{i=1}^n x_i \,\omega_{ij} \tag{2.2}$$



Figure 2.3: Structure of the single artificial neuron

The activation function is responsible to generate the suitable output for each input set. The activation function is applied on the sum of the inputs.

$$Y_{j} = f\left(\sum_{i=1}^{n} x_{i} \omega_{ij}\right)$$

$$(2.3)$$

2.6 Activation functions

The activation function is one of the main components of the neural networks. They are responsible about taking the decision to generate suitable output for a given set of inputs. There are different types of activation or transfer functions. Some transfer functions are on off transfer functions that can either generate output or cancel it dependent on the input. Other transfer functions can generate different outputs proportional or as mathematical function of the input sum.

2.7 Hard limit functions

Hard limit function are of the basic and first used transfer function in the neural networks. It is simple and based on a logical on off principle. The output of the function is one when ever its input exceeds a given value and it is zero when the sum of inputs is less than this value. The output of the function can either exist or disappear based on the strength of the input. This type of function is less used nowadays due to the lack of flexibility in output generation. Figure 2.4 below presents the curve of the hard limit activation function. The output is zero before the threshold value and flips to become 1 after the threshold.



Figure 2.4: Hard limit activation function of neural network

The transfer function whose curve is given in the figure above can be easily defined mathematically by the equation bellow:

$$f(y) = \begin{cases} 0, & y \le threshold \\ 1, & y > threshold \end{cases}$$
(2.4)

Where, the term y is used to describe the total sum of the weighted inputs of the neuron. The function "f" is the output of the neuron after the use of the transfer function. As the equation and curve show, the output is discrete and the value can change suddenly from null value to full output just at a very small difference. This fact makes the use of hard limit functions less famous and encourages finding better types of transfer function.

2.8 Limited ramp transfer function

This type of transfer function is also simple and similar to the hard limit function. The output from the neuron can change gradually with the input instead of changing suddenly between two values. The formula below gives the general form of the limited ramp transfer function that can be used.

$$f(y) = \begin{cases} O_{\min}, & y \le threshold 1\\ ay, & threshod 1 < y < threshold 2\\ O_{\max}, & y \ge threshold 2 \end{cases}$$
(2.5)

Where, O_{min} and O_{max} are the minimum and maximum possible outputs respectively. The constant "a" is an amplification factor for the input. The curve of the output in function of the neuron inputs can be seen in the next Figure 2.5.



Figure 2.5: Linear ramp transfer function

2.9 Sigmoid Transfer Function

This type of transfer functions is very famous due to its high performance with different neural network structures (Zurada, 1992). Its main advantage is that it is continuous and has different output value for each input of the neuron. Generally, sigmoid functions are limited by zero and one or by -1 and 1. The curve is increasing slightly between these two values with the increase of the input value. The output tends towards 1 when the input tends toward infinity. This means whatever the input is, the output can't exceed the unity. Such activation function is very important to guarantee that the output has a real value and can't go toward infinite or undefined value. There are mainly two sigmoid transfer functions used in neural network.

These are the tangent transfer function whose curve is similar to rotated tangent curve around the x axis. The other function is the logarithmic function that looks like a rotated logarithmic function around the x axis. The tangent transfer function is given by:

$$f(y) = \frac{1 - e^{-\alpha y}}{1 + e^{-\alpha y}}$$
(2.6)

Where, the constant α is a slope control constant that can change the slope of the curve. The curve of a tangent transfer function is shown in Figure 2.6 below.



Figure 2.6: Tangent transfer function curve

The logarithmic transfer function is similar to that of tangential function except that its limits are 0 and 1 as shown in Figure 2.7 below. The function of the transfer function can be described as:

$$f(y) = \frac{1}{1 + e^{-\alpha y}}$$
(2.7)



Figure 2.7: Curve of the logarithmic transfer function

Linear transfer functions

In this type of neural networks, the output of the neuron is defined as an amplification factor of the inputs sum. Such transfer functions give infinite outputs in some applications and can lead the neural network to unexpected results. The curve of the pure line or linear transfer functions is shown in Figure 2.8 below. The output of the neuron can be defined in function of its input by:

$$y = a^* x \tag{2.8}$$

Where, x is the sum of neuron inputs and "a" is the amplification factor of the linear ramp.



Figure 2.8: Transfer function of linear ramp (pure line)

Each one of these transfer functions performs in different ways under different conditions. Generally, the limited transfer functions are the mostly used and most suitable for different applications of artificial neural networks.

2.10 Learning Techniques of Artificial Neural Networks

One of the main problems that faced the neural network field researchers was the learning of the proposed structure. The learning is the way in which the neural network can learn to do things. It is the way in which the network is able to understand a pattern in different images or sets of data. The learning is done by finding a method to adjust the neural network parameters to their optimum values for a given task.

Artificial neural networks can be divided based on the learning method they use to two distinct types. These are the supervised learning networks and the unsupervised learning network. The supervised learning networks are also referred to be learning by example networks. The network in this type of learning is fed with sets of inputs and their desired outputs.

2.10.1 Supervised learning of neural network

The supervised learning in neural network is the mostly used type of artificial neural network. It gains its importance from the fact it uses feedback theory to find the optimum values of its parameters. Supervised learning uses well defined rules to find these parameters and to update the neural network weights according to the given input-output sets. One of the most important learning algorithms of this type is the back propagation algorithm.

2.10.2 Unsupervised learning methods

In an unsupervised learning method, the weights of the networks are updated without need for feedback rules. The inputs are fed to the network to generate the outputs that are going to be used as targets in the future.

2.11 Back Propagation Learning Algorithm

Back propagation algorithm is a well known supervised learning algorithm of the artificial neural networks. It became the most used algorithm few years after being proposed due to its strength and performance in finding the optimum weight values of different layers. Until today, the back propagation algorithm is still the most famous and powerful learning algorithm of neural network. Recent modern learning methods such as deep learning algorithm are no more than extension of the back propagation algorithm.

The term back propagation refers to the way this algorithm performs the weight updating process. An error function is defined for each single layer of the neural network. This error function is used to find the difference between the expected outputs of the layer compared to the actual output. The found error is then propagated back to the previous layer iteratively until the minimum error value is obtained in the output. Such an algorithm is shown in the Figure 2.9 below. The error value in the output layer is found by:

$$E = \sum (T - Y)^2$$
 (2.9)

Where, Y is the output layer output, T is the target expected to be present at the output of the neural network. This error function is the target to be minimized in order for the network to accomplish its goal. A propagation error is then defined by:

$$e_i = (T - Y)^* Y^{(i)}$$
 (2.10)

If we suppose that the output Y is the result of a sigmoid function that is defined by:

$$Y(x) = \frac{1}{1 + e^{-\alpha x}}$$
 (2.11)

The derivative of the output is proven then to be found by:

$$Y'(x) = Y(1-Y)$$
 (2.12)



Figure 2.9: Back propagation training algorithm structure

The error function reduces to become:

$$e_{j} = (T_{j} - Y_{j}) * Y_{j} * (1 - Y_{j})$$
(2.13)

The variation of the weight values is then found using the calculated error with respect to the neural parameters μ and η which controls the behaviour of the network training curve. The weight variation is given by:

$$\delta \omega_j^n = \mu e_j Y_{hi}^n + \eta \delta \omega_j^{n-1} \tag{2.14}$$

Where; $\delta \omega_j^n$ is the actual variation in the output weight j, $\delta \omega_j^{n-1}$ is the previous variation value of the same weight, e_j is the error found at the output related to the neuron j, and Y_{hi}^n is the output of the previous hidden layer. The parameters μ and η are the learning rate and momentum factor of the neural network. The learning rate can control the speed of convergence of the network toward its goal while the momentum factor helps avoiding the local minimum errors that can appear during the training. The new weight value is equal to the old value in addition to the weight variation value given previously:

$$\omega_j^n = \omega_j^{n-1} + \delta \omega_j^n \tag{2.15}$$

The new weight values are then used in a new iteration to find the new output and compare it with the desired targets of the neural network. The back propagation algorithm is designed in such a way to guarantee the convergence of the error to zero with each new epoch. The training process continues updating weights until the error function reaches an accepted result value.

After the end of the training process, the final weight values are generalised and accepted to be the true values for the given set of input outputs.

CHAPTER 3

DIGITAL IMAGE PROCESSING TECHNIQUES

3.1 Introduction

Image processing is one of the most important and useful sciences in our daily life. It is employed extensively in our daily life even if we can't feel it. Our mobile cameras, TV's, computers, different types of screens, scanners, printers, and many other applications are using digital image processing to present us the visual effects that we see all around us. Image processing is the mathematical representation and treatment of the image to obtain and modify its features or to ameliorate its characteristics.

3.2 Representation of Digital Image

Digital images are treated in general in the form of matrix representation in two dimensions. These two dimensional matrixes are represented in function of the space. Supposing a function g for the two independent variables x and y, the function g(x, y) can be considered the function of the image. The function g can be called intensity or impulse function. The independent variables x and y are respectively the variable denoting the row and column of the pixels in an image. In this notation, the function g(x, y) is the intensity of the light for the pixel in the position defined by the row x and the column y in an image (Gonzalez & Woods, 2001). Figure 3.1 presents the intensity convention which is the most used representation of digital images in digital computers. Based on this notation, any digital image can be represented in the form of matrix as follows:

$$g(x,y) = \begin{bmatrix} g(1,1) & g(1,2) & \cdots & \vdots \\ g(2,1) & \cdots & \cdots & \vdots \\ \vdots & & & \\ g(2,M) & & g(N,M) \end{bmatrix}$$
(2.16)



Figure 3.1: representation of digital images

In the above described image, the image consists of M lines and N columns; the numbers M and N corresponds to the size of image in pixel. Generally, the image size is described in pixels instead of distance like centimetres. The image that has a size of 1024*1024 pixels is an image that has 1024*1024 different intensity values within it.

3.2.1 Range of intensity values

In digital images, the intensity values are dependent on the representation of the image. In computers, the image intensity is a closed interval where there is a minimum and maximum value for the image intensity. In practice, the range of intensity for an image is chosen based on the goal of the image processing. The higher intensity value is generally given for the brighter pixels of an image. Higher intensity values are given for white or bright colours while lower intensity values are given to the dark pixels. In theory, it is enough for intensity values to be real positive values to describe the brightness of pixels in an image, however; the structure and hardware limitations of digital systems that use binary numbers (0, 1) imply that the number of intensity values in one image is an integer power of 2. The 8bit images have 2^{8} different intensity values while 16bit images have 2^{16} different intensity values. The values range in an 8bit image is between 0 and 2^{8} -1.

3.3 Histogram

Histogram is referred to a discrete function that presents the occurrence of changes in gray levels in an image. If the image has L different intensity levels, the histogram function defines the number of pixels that having each intensity level(Gonzalez & Woods, 2001). The histogram can give an idea about the intensity distribution of the image pixels rather than the intensity values in that image. There are different processes that can be applied on the histogram images to increase the quality of image such as histogram equalisation which is used to improve the intensity distribution of the image pixels. Histogram can be implemented in the extraction and derivation of different image features. The image processing techniques that use the histogram are in most of cases statistical techniques. They are related and based on the intensity values statistical distribution probability. One of the main advantages of the histogram image processing is the time complexity reduction. An image is two dimensional –if not more – whose processing implies the use of matrix operation on huge amount of data or pixels individually.



Figure 3.2: the histogram of a gray scale image

In the histogram, the complexity reduces to a one dimensional vector of small amount of values such as 2^k ; where k is the bit resolution of the pixel. In an 8bit image resolution, the histogram is simply constructed of 256 different values whatever the size of the image itself.

Main drawback of histogram based image processing is the need to calculate the histogram which is a time consuming process. The histogram based image processing is useful but sometimes it appears to be inadequate for complex and specific image processing targets. Figure 3.2 presents the histogram of a gray scale image where the pixels intensity is presented for all intensity values. In this histogram it is noticed that the most repeated intensity value is 0 which means that most of the image parts is black.

3.3.1 Histogram equalisation



Figure 3.3: histogram equalisation of the image and histogram

Histogram equalisation is one of the important and interesting image processing methods. It is based on the equalisation or redistribution of the image intensity values in an equal form. This will give better vision for images where unequal distribution is affecting the clearness of the image. The histogram equalisation is applied to images where visual enhancement is needed. The equalisation improves the distribution of intensities of the image as presented in Figure 3.3.

3.4 RGB Image

Human visual system is more complex and different from digital systems. Humans can extract more useful information from images and get details from colours which appear to be unimportant for digital computers. Human eyes can see images in multicolour representation rather than scale of black and white colours. The retina of the human eye has three different types of receptors or visual rods. These rods can sense three types of waves with different frequencies that correspond to the Red, Green, and Blue colours. All the other colours are then constructed in the brain by mixing intensities of these three main colours. In RGB images, the colours are made of mixture of the intensity of these three colours in each single pixel.

3.4.1 RGB to gray image conversion

The coloured images are built of three main colour intensities. Each coloured image also known as RGB image is prescribed using a mixture of these three colours. In digital computers, this mixture is represented in the form of three connected matrixes. Each matrix contains the intensity of light of the specific main colour. The processing of any coloured image means the mathematical processing of the three sub-matrixes of intensity. The complexity of the coloured image processing is at least three times more than the gray scale image with no benefit for computer operation. Thus, the conversion of RGB images into gray scale images prior to any digital processing technique is indispensable for complexity and processing time reduction without any losses in the images. Gray scale images contain the same data that is included in the correspondent coloured image. The conversion from coloured image into gray scale image is applied with respect to sensitivity degree of each one of the three receptor types of the retina. It was found that the green colour receptors are more sensitive than the other two receptors while the blue colour rods are the least sensitive receptors (Khashman & Dimililer, 2008). Thus, in any conversion process, the sensitivity is a vital factor that can affect the human vision of a gray scale image. The equation used to convert colour image into gray scale image is given by:

$$I = 0.299 * R + 0.587 * G + 0.114 * B \tag{2.17}$$

The given factors of each colour are designed based on the sensitivity of each type of retina rods to each one of the three main colours. Based on this idea, the gray scale image is bright

and exactly clear like the original coloured image and is based on the contribution of each colour in the original image rather than the average of these colours.

3.4.2 Image segmentation

One of the most important requirements of image processing tools is the capability to analyze these images and find specific regions within those images. These regions can be found based on some specific features. In fact, there is a great variety of techniques that enable computers to separate different regions of an image. Different algorithms are nowadays used to extract abnormal parts and other malformations from the medical images. These regions are used to be named Regions of Interest ROI.

Image segmentation is the process that sub-divides an image into small parts or structural regions. These regions or units share specific features based on which they can be classified. There are several segmentation methods that are used in the modern image processing based on the goal of segmentation. Mainly, three basic categories can be found in image segmentation (Ferrari, Rangayyan, R.M. Desautels, Borges, & Frere, 2004):

- 1- Thresholding techniques
- 2- Boundary segmentation methods
- 3- Region segmentation methods

3.4.3 Thresholding

The main idea in thresholding segmentation is to separate that image pixels based on predefined ranges of intensity. The pixels that fall in a range of intensity values are all assigned one intensity value. This is applied on different intensity ranges based on the application and other requirements of the specified image. Mathematically, the thresholding process is defined by:

$$t(x,y) = \begin{cases} i, g(x,y) \in [L_1, L_2] \\ j, g(x,y) \in [L_3, L_4] \end{cases}$$
(2.18)

Where all the intensity values that belongs to the range L_1-L_2 are assigned the value I, while all the intensity values that belong to the range L_3-L_4 are assigned the value j. thresholding is used in different image processing applications due to its simplicity and results. For better understanding of the thresholding image segmentation, Figure 3.4 represent the original and threshold image of brain. It is clear that the threshold image is clearer and brighter than the original image with focused details. The basic idea in thresholding makes it more suitable for segmenting regions of interest with distinct intensity values from the other parts of the image.



(a) Original Image





Boundary segmentation methods 3.4.3.1

In the field of digital image processing, boundary in an image is known as a one incessant border that forms a closed path that encounters a part of the image. The enclosed part can be considered as region of interest. An edge in digital image is the region where transition happens between light and dark pixels of the images.

In boundary segmentation, the image is initially scanned to find the sharp transitions in pixel intensity. This scan is applied to detect the edges that have specific features like orientation, blur, and other features. After the scan process, edge linking methods are used to create closed regions of boundary. It is important to notice that the ideal boundary edges that enclose regions of interest are impossible to be found. This rends the edge detection process to be more complex (Ferrari et al., 2004).

3.4.3.2 Region segmentation methods

In most of the cases, the regions of interest in an image that we need to extract have specific features or textures from the other parts of the image. Thresholding segmentation and boundary detection methods are in most of cases unable to find specific textures as they are considered as local properties (Gonzalez & Woods, 2001). In such cases, the region based image segmentation can be useful and applied. In this method, an assumption is made that all pixels in the ROI share similar features to simplify the process of segmentation. The group of pixels that share similar features in an image are known by neighbourhood in the region based image segmentation.

3.5 Canny Edge Detection

Canny edge detection is one of the most famous segmentation algorithms. It is based on the separation of different parts of image into groups. The main purpose of this algorithm is to separate some specific parts or areas of an image. The segmented areas are important to specify some image parts like faces and tumors. It is also useful in finding edges of the different parts in the image. The unwanted parts of the image can be easily eliminated by replacing their pixels by zeros. Thresholding process implements the useful logic of eliminating the intensity value if it is less than a specific value; And keeping that value if it is brighter than the threshold. As said earlier, edges in the image are the places where sharp intensity variations occur. The intensity variation is the index for differences in the features of an image.

Canny edge detection is the mostly used technique for the detection of edges in digital imaging. Canny operator is known to increase the signal to noise ratio and find the edges precisely in an image. It consists of different processing steps that can be described below:

The image in the first step is treated such that it becomes smooth and blur is removed from the image to decrease the noise contained in its pixels. In order to smooth the image, a Gaussian filter is applied to the image through simple convolution of the filter with the image pixels. In the next stage the gradient of each single line and column in the image is derived. As it is well known, the gradient is function of the difference between neighbour values. Whenever the gradient is high this leads to the fact that a great change in pixels values has happened in the region. Next step involves the derivation of the gradient of each line and column of the image. Thus, the edges are fund through the gradient calculation in every point of the image. A thresholding technique is finally applied to eliminate the weak gradient points and emphasize

the strong and sharp edge regions. Double threshold is generally applied in Canny edge detection algorithm. Canny edge detection is an important and very efficient algorithm in the detection of image edges and noise cancellation. This method is also very accurate in finding the edges in digital images (Khashman & Dimililer, 2008). Figure 3.5 below shows the segmentation results using canny operator on the brain MRI image. The result of segmenting the image is clear to be accurate and perfect with all edges drawn correctly.



(a) Original Image



(b) Canny edge segmented Image

Figure 3.5: Original image vs. Canny segmented image

3.6 Resizing the Images into Small Size

The original MRI images are large enough to be analysed manually by experts with high resolution and suitable size for human visual system. In computer systems especially when it comes to neural networks, processing large scale images is a very costly process that needs huge material and software efforts. However, it is very clear that computer is different from biological brain system in images analysing. In a computer system it is enough to extract the important features of the image in any suitable size to do the job. Thus, in neural networks the used images are generally resized to small sizes that are mostly difficult to be analyzed by humans. The resizing process applies an averaging algorithm that ensures the transfer of the features of each pixel in the original image to the new small image. Averaging is well known in mathematic as the mean of a set of values. It is considered as a short description of multiple values and gives a good idea about these values. In image processing, this process is

implemented to decrease the image complexity without losing any of its fundamental features. A moving window of suitable size is convolved with the original image to create a small version of the image. The moving window is applied both vertically and horizontally on the whole image pixels. All the features of the original image are included in the new image.

Averaging algorithm is very constructive and useful with artificial neural network applications as it reduces the complexity of the studied network hundreds of times. The neural network will perform faster with less material requirements without losing its accuracy with small versions of images. The moving window is constructed simply by using the next structure and convolving it with the image.

$$Window = \frac{1}{N^2} \begin{bmatrix} 1_{11} & 1_{12} & & 1_{1N} \\ \vdots & \vdots & \vdots & \vdots \\ 1_{N1} & \cdots & \cdots \\ 1_{N1} & \cdots & \cdots \end{bmatrix}$$
(2.19)

3.7 Wiener Filter

Image filtering is one of the most important digital image processing techniques. Filtering is the process of removing different types of noise from an image to improve its visibility. Noise can be the effect of movement during image capture or the result of transmission through different channels, blur, analogue to digital conversion, and many other reasons. Weiner filter enhancement implements Weiner adaptive algorithm to eliminate the detected noise from noisy image. The performance of the filter is then function of the accuracy of the noise estimation process. Wiener filter has proven its capability to remove different types of noise from images with high accuracy.

The Weiner filter can be described as a frequency domain based weighting function. It is based on the assumption that the energy of spectral density of the noise signal is higher at high frequency. The filter has better attenuation if the spectral density of a signal is smaller. Wiener filter is an optimum filter that is used for linear estimation of wanted signal. In wiener filter approach, the signal S_x is assumed to be noised by the signal S_n . the noise signal is considered to be zero mean and having a standard deviation δ . The application of wiener filter will produce a pure signal (free of noise). Wiener filter is applied on window or small part of the image whose choice is function of the noise characteristics (Santra, 2013).

Wiener filter is an adaptive filter based on the approximation of the mean squared error algorithm. It is a kind of stationary enhancement filter for noisy images with blur or additive noise type. Wiener filter is a frequency space filter that is used with the spectrum of a digital image. Weiner filter was firstly presented as an optimum filter for image restoration and filtering by (Fechner, 1993; Khajwaniya & Tiwari, 2015; Wang, Peng, Wang, & Peng, 2015). Using wiener filter, the local mean and standard deviation values are estimated around each pixel. Based on these estimated values, the filter creates a new value of the pixel as shown in the next formulas.

$$m = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} a(i,j)$$
(2.20)

$$\sigma^{2} = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} a^{2}(i,j) - m$$
(2.21)

Where; *M* and *N* are the two dimensions of the wiener window, m and σ^2 are the average and standard deviation of that window pixels. The estimate of the new pixel value is then given by:

$$x(i,j) = m + \frac{\sigma^2 - v^2}{\sigma^2} (\Delta m)$$
(2.22)

Where; the term Δm refers to the difference between the pixel value and the local mean of that value or the deviation of the pixel from its local mean value. It is important to remember here that the Wiener filter is based on an estimation of the noise in the local neighbourhood of the concerned pixel. Figure 3.6 below shows the application of wiener filter on a noisy image with Gaussian noise.



(a) Noisy image



(b) Wiener filtered image

Figure 3.6: Wiener filtering of noisy images

3.8 Wavelet Transform

In mathematics, the waves are presented as oscillating curves or functions of time. Wavelet is a type of wave that processes the concentrated energy in the time. The characteristics of wavelets allow at the same time the study of the signal in time and frequency domain. This is mainly due to the reality that the wavelet is periodic time function that concentrates the energy. The Wavelet transform provides a flexible mathematical tool to understand transients, and non stationary signals (Bergh, Ekstedt, & Lindberg, 1999).

Wavelet transform can be applied on digital images to offer some analysis tool and extract some kind of features. Transform idea of an image is carried out by the transformation of the image with respect to some features. The features are chosen in a way that guarantees an efficient pixel values de-correlation, in other words; expressing the image in a compact version of it. Wavelets are functions that are generated beginning from a single function. This single function is called the mother wavelet. Wavelets are generated by scaling and translation in time or frequency domain of the mother function (J. C. Goswami & Chan, 2011).

If the mother function is given by $\psi(t)$, the other wavelets $\psi_{a,b}(t)$ can be given by (Lee & Yamamoto, 1994):

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \psi(\frac{t-b}{a})$$
(2.23)

Where "a" and "b" are real arbitrary numbers representing the dilation and shift parameters of the wavelet. The wavelet transform of a function or a signal is then given by:

$$W(a,b) = \int_{-\infty}^{\infty} \psi_{a,b}(t) f(t) dt$$
(2.24)

The HAAR Wavelet Transform (HWT) is a transformation from the space domain to the frequency domain. It divides each signal or set of data into two pieces of information, the first is known as average or approximation; the second is called the difference or detail.

The wavelet transform is similar to the Fourier transform with a absolutely distinctive authenticity function. The main difference is that Fourier transforms divide the signal into sinus and cosines, on the other hand, the wavelet transform employs functions that are limited as a part of both the real and Fourier space. The figure 3.7 below represents the result of applying Wavelet transform on the image a, the image b shows the resulting details and approximations.



(a) Segmented image

(b) Wavelet transform image

Figure 3.7: Application of wavelet on the segmented image of brain In discrete HAAR transform, the approximations and details of a discrete signal of length N can be given by:

$$a_n = \frac{f_{2n-1} + f_{2n}}{\sqrt{2}}, n = 1...\frac{N}{2}$$
(2.25)

$$d_n = \frac{f_{2n-1} - f_{2n}}{\sqrt{2}}, n = 1...\frac{N}{2}$$
(2.26)

The same formulation is applied for matrix representation of images in rows and columns to create the HAAR Wavelet transform of the images.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter will present the results of the work in this thesis. All practical results of the application of neural network will be presented and discussed in this chapter. Different experiments will be carried out under different parameters and image processing characteristics. The results will be tabulated, discussed, and evaluated in this chapter.

4.2 Description of Database

In the proposed system, 118 benign brain tumor images and 56 malignant images were used. These images were all classified based on the experience of specialists and separated carefully.



(a) Malignant tumor



(b) Normal image

Figure 4.1: Sample of our database images

Figure 4.1 shows a sample of the two different images from our database. In this work, all data base images will be treated using different image processing techniques in combination with artificial neural networks to classify these images. The classification and processing goal is to offer an automated decision system that can help medicines in giving their final decisions concerning the brain tumor in its different stages. It is also needed to help in the early

detection of the brain tumor; the thing that can reduce the number of brain tumor caused death cases.

In order to be able to judge the proposed topology, different experiments will be applied on the database images. In each experiment different parameters of the image processing and neural networks will be used. Figure 4.2 presents the different images obtained after each one of the steps during the image processing of our database images. First of all, the original image is read from the database and scaled down to reduce the processing cost. The size of 256*256 was chosen for the processed images in the first step. After resizing the database images, all images were converted to gray scale images in which the colours are represented as a scale between the white and black colour. These images offer low cost processing with the same performance of the coloured images because the computer doesn't recognize colours. The processing of gray scale images is three times faster than processing of their RGB versions.



Figure 4.2: Images obtained from the image processing

The gray scale images are then filtered using wiener filter to eliminate any type of unwanted noise or disturbances in the images. One further step is applied to detect the important edges in the filtered images using "Canny" edge detection method. Finally, the images are processed

using wavelet transform that split each image into four different sub images. The 256*256 images reduce to 64*64 images that are suitable for neural network application.

4.3 Training of Database Images

The whole dataset images were divided into two separate parts. One part was used as example for the training of the proposed back propagation algorithm. The other part was reserved for the test of the trained network performance. The test is generally designed to check whether the trained network is able to recognize correctly unknown images out of the training set. The importance of the neural network resides in this point as it should be valid for unknown database images. Neural network was applied after each step of the image processing to examine the effect of each one of the processing methods on the performance of the neural network.

4.4 Preparation of Processed Images for the Neural Network

The structure of the artificial neural network allows it to accept special structures of data to accomplish required tasks. The input of the neural network as discussed earlier should be a vector of one dimension whose elements are the dataset elements. The 2D images needs to be converted to 1D vector in order to be fed to the input layer of the network. The image to vector conversion is a simple process that arranges all the image columns in one long column that contains all the features of the image. In neural network applications, it was found that the use of normalised input data is a time and cost saving process. For this reason, all input pixel values will be normalized to the range [0, 1] before being fed to the network.

The normalized images (or vectors) should be arranged in successive order to be fed one by one to the network with respect to their designed targets. The targets are built manually of chosen codes of binary values. As there are two choices for the images (benign and malignant), two different codes are enough to identify the two different cases. Simply, the binary value 0 was associated with the benign images to indicate the absence of malignancy. On the contrary, the value 1 was assigned to all malignant images to signify the existence of malignancy.

4.4.1 ANN with wiener filtered images

In this experiment, the artificial neural network was applied on the images after applying wiener filtering on the database images. No edge detection or wavelet transform was applied on the images in this experiment. The parameters of the neural network are presented in Table 4.1. The network was composed of one input layer, two hidden layers and 1 output layer. The size of hidden layers was 10 and 150 neurons respectively. The output layer size was chosen to be 1 neuron with binary output of either 1 or 0. Figure 4.3 shows the neural network tool of MATLAB during the training of the network.



Figure 4.3: Neural network tool during the training process

Fable 4.1: Par	ameters of the	neural networ	k with	wiener	filter
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Number of layers	4	Input layer size	2116
Hidden layers size	[10 150]	MSE goal	0.001
Transfer functions	[tansig, tansig, tansig]	Learning rate	0.01
Output layer size	1	Momentum factor	0.25
Training images	118	Test images	56
Training performance	100%	Test performance	96.4%

After the end of the training process, the trained network was able to classify all the training images correctly. 118 images out of 118 training images were truly identified. The test performance reached the level of 96.4% with 54 correctly classified images out of 56 test images. The Figure 4.4 below presents the MSE curve obtained during the training of the neural network. The curve shows that the convergence of the network was fast and perfect within less than 240 iterations.



Figure 4.4: MSE curve during the training of ANN (Wiener)

4.5 ANN with Canny Edge Detection

In this part, training and test processes are applied on the images after being filtered using Wiener filter and segmented using "Canny" segmentation process. The parameters of the training are shown in Table 4.2.

Number of layers	4	Input layer size	2116
Hidden layers size	[10 150]	MSE goal	0.001
Transfer functions	[tansig, tansig, tansig]	Learning rate	0.01
Output layer size	1	Momentum factor	0.25
Training images	118	Test images	56
Training performance	100%	Test performance	89.3%

Table 4.2: Parameters of the neural network "Canny"

The training of the neural network has given a training performance of 100% while the test performance was as low as 89.3%. 50 test images out of 56 images were correctly recognized in this case. The MSE curve showed in Figure 4.5 shows that the training in this case was slower than the wiener filter experiment. The network took approximately 2200 iterations before reaching the targeted MSE goal.



Figure 4.5: MSE curve of the training (Canny)

4.6 ANN with Gray Scale Images

The gray scale images that were obtained by converting the RGB images and resizing them to small size were fed directly to the neural network without applying the Wiener filtering, segmentation, or Wavelet transform. The use of these images without processing is less costly but suffers from the possibility of disturbance that needs to be adjusted prior to the neural network training. The same parameters were applied on the gray scale images as shown in Table 4.3. two hidden layers whose sizes are 10 neurons and 150 neurons respectively were implemented. the input layer contained 2116 neurons while the output layer was composed of a single neuron.

Number of layers	4	Input layer size	2116
Hidden layers size	[10 150]	MSE goal	0.0114
Transfer functions	[tansig, tansig, tansig]	Learning rate	0.01

Table 4.3: Parameters of the neural network "Gray images"

Output layer size	1	Momentum factor	0.25
Training images	118	Test images	56
Training performance	98.3%	Test performance	83.9%

The training performance of this experiment has shown good results with 98.3% accuracy. 116 images were correctly recognized out of 118 training images. In the test, the performance of gray scale images was less than expected with just 83%. This means that 9 images out of the 56 test images were not recognized correctly. The behaviour of the network during the training of gray scale images can be noticed from the MSE curve shown in Figure 4.6 where the curve has step shape. The training didn't reach the expected MSE goal after 5000 iterations.



Figure 4.6: MSE curve of the training process (gray scale)

4.7 ANN with HAAR Wavelet

In this experiment, the database images were all filtered using Wiener filter, segmented using "Canny" edge detection method, resized and processed through the application of HAAR wavelet transform. The different image processing steps were applied to enhance the images and ameliorate the performance of neural network classification task. Segmentation of the images is useful to concentrate on some areas of interest in the images preparing for the identification of these areas. The training of neural network was applied on the images using the parameters shown in Table 4.4. Two hidden layers of tangent sigmoid transfer function

were used in the hidden layers. Tangent sigmoid was also used in the output layer for its performance. The results obtained during the training and test of this network show that the network has achieved a training performance of 100% and test performance of 98.2%.

Number of layers	4	Input layer size	2116
Hidden layers size	[10 150]	MSE goal	0.0114
Transfer functions	[tansig, tansig, tansig]	Learning rate	0.001
Output layer size	1	Momentum factor	0.25
Training images	118	Test images	56
Training performance	100%	Test performance	98.2%

 Table 4.4: Parameters of the neural network "HAAR wavelets"

The MSE curve presented in Figure 4.7 below shows the behaviour of the neural network during the training of the system. The MSE was decreasing smoothly during the training drawing a smooth and perfect curve. The MSE reached a minimum of 0.0001 in approximately 1788 iterations.



Figure 4.7: MSE curve of the training process (HAAR)

CHAPTER 5

CONCLUSIONS

Neural networks have become very famous in the medical field due to their results in the detection and classification of different diseases. They have been implemented in the detection and classification of different types of diseases especially cancer diseases, skin diseases, and other different infections. This work presents the implementation of artificial neural networks for the detection of brain tumor infections. Brain cancer is one of the most dangerous types of diseases that affect the brain which is the computer that controls all the body. The brain tumors are divided into two types: benign and malignant tumors. The detection of the type of the tumor is a very tough process that requires a lot of experience in the cancer diseases. The implementation of computer based decision support systems is important to help medical doctors in their decisions.

Brain cancer has attracted the attention of researchers to implement different technologies in the detection process. Artificial neural networks were presented in different researches and discussed for the detection of brain tumors and their classification. They have shown high accuracy with good results in the classification and detection of brain tumor types. In this work, the implementation of back propagation algorithm for the detection of brain tumor based on image processing was presented. 174 magnetic resonance brain images were used and implemented in this work. These images were classified into 118 benign images and 56 malignant images. All the database images were treated using wiener filter for enhancement, binary segmentation for the detection of the image. Different image processing techniques were also used in this work to help preparing the images for better implementation with ANN. these techniques included the use of averaging algorithms for image resizing, the use of normalisation methods to normalise pixel values of the images, and matrix conversion for the transfer of matrix to vector before feeding the ANN.

The back propagation algorithm was applied on the treated images in different stages in order to examine the effect of each image processing technique on the system performance. The results have shown the efficiency of neural network in the detection process and the effect of image processing on this efficiency. The neural networks implementation has given a detection efficiency of 82% with the raw gray scale MR images. This efficiency was increased to 98% after the implementation of different stages of image processing. Obtained results have shown the effect of image filtering and segmentation on the performance and time efficiency of the neural network.

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