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Brain Tumors Detection using Artificial Neural Networks

كشف أورام الدماغ باستخدام الشبكات العصبية الإصطناعية

A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR M.SC. IN BIOMEDICAL ENGINEERING

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Abstract

Brain tumor is one among the most dangerous diseases in the world, patient's life can be saved if the brain tumor is detected and diagnosed properly in its earliest stages. Since brain has the most complex structure in which tissues are interconnected rigorously. Thus makes the brain tumor detection a challenging task. Brain tumor detection and classification requires clinical experts to meet the standard level of accuracy.

This limitation is overcome by the use of Computer Aided Diagnosis Systems (CAD Systems) in the diagnosis of brain tumors. In this thesis propose an efficient method for brain tumor detection, also the thesis is interesting in determines which type of artificial neural network is the best for image recognition, Neural network must be able to determine the state of brain according to magnetic resonance imaging and determine whether it normal or abnormal state.

Data collection was from Harvard citations,cancer imaging archiveand figshare date base.

From each MR image texture features are extracted using Gray Level Co-occurrence Matrix to prepare training data which was introduced to neural network as input and target vectors. Three neural network are designed and trained using MATLAB feature nntool which are Cascade feed forward, Feed forward and Learning vector quantization, After testing, the Feed forward network achieved performance ratio equal 97.91 %, also Cascadefeed forward ratio was 96.88%, while Learning vector quantization performance ratio was reach to 56.25%.

المستخلص

ورم الدماغ هو أحد الأمراض الأكثر خطورة في العالم ، ويمكن إنقاذ حياة المريض إذا تم اكتشاف ورم في الدماغ وتشخيصه بشكل صحيح في مراحله المبكرة. بما أن الدماغ لديه البنية الأكثر تعقيدًا والتي تترابط فيها الأنسجة بصرامة. مما يجعل اكتشاف ورم الدماغ مهمة صعبة. يتطلب الكشف عن أورام الدماغ وتصنيفها من الخبراء السريريين استيفاء مستوى الدقة القياسي.

يتم التغلب على هذا القيد من خلال استخدام نظم التشخيص بمساعدة الكمبيوتر (CAD) في تشخيص أورام المخ. في هذه الأطروحة تقترح طريقة فعالة لاكتشاف ورم الدماغ ، كما أن الرسالة مثيرة للاهتمام في تحديد أي نوع من الشبكات العصبية الاصطناعية هو الأفضل للتعرف على الصور ، يجب أن تكون الشبكة العصبية قادرة على تحديد حالة الدماغ وفقا للتصوير بالرنين المغناطيسي وتحديد سواء كانت حالة طبيعية أو غير طبيعية.

تم جمع الصور من موقع Cancer image archive , Harvard و Figshare قاعدة بيانات

من كل صورة الرنين المغناطيسي يتم استخراج خصائص النسيج باستخدام مصفوفة التواجد ذات المستوى الرمادي لإعداد بيانات التدريب التي تم إدخالها إلى الشبكات العصبية كمدخلات وناقلات مستهدفة. ثلاث شبكات عصبية تم تصميمها وتدريبها باستخدام أداة الشبكة العصبية المتوفرة في الماتلاب التي هي عبارة عن Cascade feed forward ، Feed forward وLearning vector quantization ، وبعد الاختبار ، حققت شبكة Feed forward نسبة أداء تساوي 97.91٪ ، نسبة Feed forward Cascade كانت 96.88٪ ، بينما Learning vector quantization نسبة أداء كانت تصل إلى 56.25

Chapter One

Introduction

1.1 General View

Digital Image processing is an emerging field in which doctors and surgeons are getting different easy pathways for the analysis of complex disease such as cancer, brain tumor, breast cancer, kidney stones, etc. The detection of brain disease is a very challenging task, in which special care is taken for image segmentation.

A particular part of body is scanned in the discussed applications of the image analysis and techniques such as MRI, CT scan, X rays. The images are judged by physicians or surgeons to solve the problems. Brain tumor is a big cause of disability and death worldwide and related abnormalities constitute for major changes in life.

The classification and detection of the tumor is very expensive. MRI is an advance technique to detect the tissues and the disease of brain cancer.

MRI provides the different information about different structures in the body which are achieved with the help of an X-ray, computed tomography (CT) scan, Ultrasound but MRI is the best technique for higher quality of its images and has the advantage of lack of side effects on the body tissues.

MRI technology has a magnetic field and train pulses of radio wave energy that makes pictures of structures and organs within a body.[1]

In the diagnosis analysis of MRI images, segmentation of image is required and analysis of image segmentation is very important part of any type of detection in image analysis. Image segmentation techniques help to get the meaningful information, which is very much easy to analysis.

Segmentation of tumor can be done based on the edge detection technique. It also segments other unknown regions too and limited to justify the brain tumor in a particular direction of left and right.

When the algorithm is applied, the position of tumor should be known for the perfect detection in left or right direction. Finding of multiple tumors is also challenging and most of techniques user interface. Biomedical imaging processing in MATLAB is the integrated solution of the problems in tumor detection, Human cell is having cancer as a major disease. The human body is a group of cells united together to form organs and tissues such as bones and muscles, liver and the lungs. In each cell order, Genes inside each the cell work, reproduce, grow, and die. Generally, human cells follow these orders, and persons remain healthy. [2]

Sometimes, these instructions are mixed together and causing the cells to form lumps or tumors, and spreading through the lymphatic system and bloodstream to another regions of the bogy.

Tumors can be either malignant (cancerous) or benign (noncancerous).

The tumor cells which stay in one place in the body are called benign and are not generally life-threatening.

The tumor cells are able to invade nearby tissues called malignant and scattered and spared to another parts of the body.

The cancer cells, which are spreading over other parts of the body, are called metastases. Brain is affected by the brain cancer starts in the human brain cells.

The brain is a soft collective mass of neurons (nerves) and glial cells or supportive tissue, covered by membranes and protected by the skull. [1]

1.2 Problem Statement

The difficulty of distinguishbrain tumor among brain tissue.

1.3 Objectives

1.3.1 General Objectives

The main purpose of this thesis is to design automatic algorithm system to detect brain tumor abnormality using artificial neural networks.

1.3.2 Specific Objectives

The specific objectives are to:

1- Detect brain tumors from magnetic resonance image.
2- Develop a structure approach to analyze the experiments data.
3- Develop better feature extraction and classification algorithm for an input image.
4- Detect brain tumor by artificial neural Network's to increase the accuracy and yield.
5- Design graphic user interface window (GUI) for detection method.

1.4 Methodology

The proposed algorithm starts by reading the input brain MR image and converting it into grey scale image. There are four major steps in the proposed approach. The first step is image pre-processing, the second step is brain tissue segmentation, the third step is feature extraction and the forth step is classification.

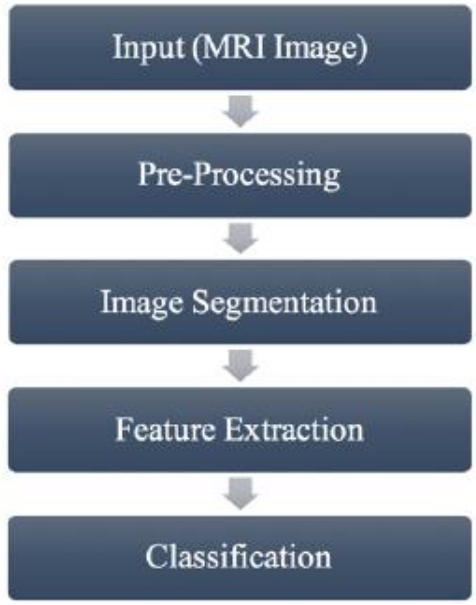

Figure1.1 Steps for image processing.

1.5 Thesis Layout

This thesis consists of six chapter’s chapter one is an introduction, Chapter two is consists of literature reviews, Chapter three is speak about theoretical background, Chapter four consists of Methodology, Chapter five is results and discussion, Finally conclusion and recommendation in chapter six.

Chapter Two

Literature Reviews

Many studies were done and used artificial neural networks forpurpose of image analysis and recognition, which was introduced in the following:

1-Kalpana U. Rathod, Prof. Y. D. Kapse, MATLAB Based Brain Tumour Extraction Using Artificial Neural Network, International Journal on Recent and Innovation Trends in Computing and Communication, 2016.

Brain tumour is the major cause of mortality among children and adults. The chance of survival can be greater when the tumour is detected correctly at its early stage. This paper presents a neural network techniques for the classification of magnetic resonance brain image. The proposed technique consists of three stages, features extraction from gray scale MR Image using gray level co-occurrence matrix, MR image segmentation using k-mean clustering method and classification of MR Image into normal and abnormal (tumourous) image using feed-forward neural network. This technique have been developed on MATLAB version 7.5.0 platform.[2]

2-Naveena H S, Shreedhara K S, Mohamed Rafi, Detection and Classification of Brain Tumor using BPN and PNN Artificial Neural Network Algorithms, International Journal of Computer Science and Mobile Computing, 2015.

A brain tumor, defined as an abnormal growth of cells within the brain or the central spinal canal. We exploit the capability of artificial neural network approach namely Back propagation neural network (BPN) and Probabilistic Neural network (PNN) to classify brain MRI images to either cancerous or noncancerous tumour. Image segmentation plays a significant role in image processing as it helps in the extraction of suspicious regions from the medical images. In this paper we have proposed segmentation of brain MRI image using K-means clustering algorithm. The extraction of texture features in the detected tumor has been achieved by using Gray Level Co-occurrence Matrix (GLCM).The proposed methodology worked in two stages Training and Testing. Both the testing and training phase gives the percentage of accuracy on each parameter in neural networks, which gives the idea to choose the best one to be used in further works.[3]

3-ArchanaA.Mali, Prof.S.R.Pawar, Detection & Classification of Brain Tumour, International Journal of Innovative Research in Computer and Communication Engineering, 2016.

The use of digital images has become a subject of widespread interest in different areas such as medical technological application and many others. There are lots of examples where image processing helps to analyze interpret and make decisions. The main use of image processing is to improve the quality of the images for human interpretation, or the perception of the machines independently. In this paper, it is intended to summarize and compare the methods of automatic detection of brain tumor through MRI. Brain Image classification techniques are studied. Brain tumor detection in MR imaging is important in medical diagnosis because it provides information associated to anatomical structures, necessary for treatment planning and patient follow-up. In this project a brain tumor Detection and Classification System is developed. The image processing techniques such as preprocessing and feature extraction have been implemented for the detection of brain tumor in the MRI images. In this paper extraction of texture features in the detected tumor is achieved using Gray Level Co-occurrence Matrix (GLCM).SVM and K-Nearest neighbor classifier is used to classify MRI brain image into abnormal and healthy image.[4]

4-Ms. Sangeetha C., Ms. Shahin A., Brain Tumor Segmentation Using Artificial Neural Network, International Research Journal of Engineering and Technology (IRJET), 2015.

Image segmentation plays a vital role in medical images. Modified K-means Clustering is used for image segmentation. Clustering is the popular unsupervised technique. The Modified K-means is to improve the effectiveness and efficiency for image segmentation. Medical imaging technique is most commonly used to visualize the internal structure and functionof the body. Magnetic Resonance Imaging (MRI) provides much greater contrast between the different soft tissues of the body. Brain Tumor is one of the serious disease causes death among the people. Tumor is an uncontrolled growth of tissue in any part of the body. In this clustering method, the MRI images are used to identify the tumor of the brain. The MRI image of the brain is given as input. The system should process the input image and detect the tumor. This method can even detect the smallest abnormality in the earlier stage itself. The different abnormality MRI scans of brain of the patients are taken for processing. Experimental results have shown that the proposed methodology is effective and more robust.[5]

5-Prof. VrushaliBorase, Prof. GayatriNaik. Prof,VaishaliLondhe, Brain MR Image Segmentation for Tumor Detection using Artificial Neural, International Journal Of Engineering And Computer Science, 2017.

A Brain Cancer is very serious disease causing deaths of many individuals. The detection and classification system must be available so that it can be diagnosed at early stages. Cancer classification has been one of the most challenging tasks in clinical diagnosis. At present cancer classification is done mainly by looking through the cells' morphological differences, which do not always give a clear distinction of cancer subtypes. Unfortunately, this may have a significant impact on the final outcome of whether a patient could be cured effectively or not. This paper deals with such a system which uses computer based procedures to detect tumour blocks and classify the type of tumour using Artificial Neural Network Algorithm for MRI images of different patients. Different image processing techniques such as image segmentation, image enhancement and feature extraction are used for detection of the brain tumour in the MRI images of the cancer affected patients. Medical Image Processing is the fast growing and challenging field now days. Medical Image techniques are used for Medical diagnosis. Brain tumour is a serious life threatening disease. Detecting Brain tumour using Image Processing techniques involves four stages namely Image Pre-Processing, Image segmentation, Feature Extraction, and Classification. Image processing and neural network techniques are used to improve the performance of detecting and classifying brain tumor in MRI images.[6]

6-Lugina Muhammad ,Retno Novi Dayawanti, Rita Rismala, Brain Tumor Detection and Classification in Magnetic Resonance Imaging (MRI) using Region Growing, Fuzzy Symmetric Measure, and Artificial Neural Network Backpropagation, International Journal of Science and Research, 2016.

Brain tumor is one type of malignant tumors that occurs because there is an abnormal and uncontrolled cell division activity. There are several ways to diagnose brain tumors, for example use MRI images. Through the MRI images, the radiologist can see the brain anatomy without performing surgery. However, this process is still done manually and could lead to misdiagnose. In addition, the different characteristics of brain tumor makes the diagnose more difficult. Therefore, we need a system of Computer- Aided Diagnostic (CAD) that will help radiologist indentifying brain tumors. In general, the CAD system consists of two major processes, namely image segmentation and feature extraction and classification. One example of segmentation is Region Growing that will classify the pixels based on certain criteria. However, the manual selection of seed point is a drawback of this method. The examples of feature extraction methods are Fuzzy Symmetric Measure (FSM), and First and Second Order Statistics. FSM values can be used to calculate the symmetry of the image brain, while the first and second order to represent feature in the image. As for the classification process, Artificial Neural Network Backpropagation method is widely used for its ability to resolve nonlearningdan complex problems. This research implements CAD system that uses Region Growing, Symmetric Fuzzy Measure, and Backpropagation Neural Network for detecting and classifying the brain tumors. In addition, the modification of converging square is conducted to select a seed point automatically.

After testing, the system generates a100% accuracy and BER is 0 in the case of distinguishing between normal and tumor brain. Besides, the average accuracy in classifying the types of brain tumors achieved 89.72% , the BER 0.1 for training data, and the average accuracy of 84.44%, BER 0.16 for the testing data. [7]

7- Virupakshappa, Dr. BasavarajAmarapur, Computer Based Diagnosis System for Tumor

Detection &Classification: A Hybrid Approach, International Journal of Pure and Applied Mathematics, 2018.

Brain tumor is one among the most dangerous diseases in the world, patient’s life can be saved if the brain tumor is detected and diagnosed properly in its earliest stages. Since brain has the most complex structure in which tissues are interconnected rigorously. Thus makes the brain tumor detection a challenging task. Brain tumor detection and classification requires clinical experts to meet the standard level of accuracy. This limitation is overcome by the use of Computer Aided Diagnosis Systems (CAD Systems) in the diagnosis of brain tumors.

In this paper we propose an efficient method for brain tumor detection and classification using hybrid method in which segmentation is carried out using Spatial Fuzzy Clustering, texture features are extracted using Gabor feature extraction method and finally classification using Artificial Neural Network (ANN) classifier. The system performance is examined with 40 trained images with 60 tested MRI scanned images. The comparative analysis in terms of accuracy with reference to the confusion matrix is presented in result section. From the experimental results we were able to achieve proposed system's accuracy level up to 92.5%.[8]

8- Said Charfi, Redouanlahmed and LalithaRangarajan, AnovelApproxhFor Brain Tumor Detection Using Neural Network, International Journal of Research in Engineering & Technology, 2015.

Computer-aided detection/diagnosis (CAD) systems can enhance the diagnostic capabilities of physicians and

reduce the time required for accurate diagnosis. The objective of this paper is to review the recent published segmentation and classification techniques and their state-of-the-art for the human brain magnetic resonance images (MRI). The review reveals the CAD systems of human brain MRI images are still an open problem. In the light of this review we proposed a hybrid intelligent machine learning technique for computer-aided detection system for automatic detection of brain tumor through magnetic resonance images. The proposed technique is based on the following computational methods; the histogram dependent thresholding for image segmentation, the discrete wavelet transform for features extraction, the principal component analysis for reducing the dimensionality of the wavelet coefficients, and the feed forward back-propagation neural network to classify inputs into normal or abnormal. The experiments were carried out on 80 images consisting of 37 normal and 43 abnormal (malignant and benign tumors) from a real human brain MRI dataset.

The classification accuracy on both training and test images is 90% which was significantly good. The results revealed that the proposed hybrid approach is accurate and fast and robust. Finally, possible future directions are suggested.[9]

9- BuketDogan, OnderDemir, SedaKazdalCalik, Computer Aided Detection Of Brain Tumors Using Morphological Reconstruction, Uludağ University Journal of The Faculty of Engineering, 2016

Computer aided detection (CAD) systems helps the detection of abnormalities in medical images using advanced image processing and pattern recognition techniques. CAD has advantages in accelerating decision-making and reducing the human error in detection process. In this study, a CAD system is developed which is based on morphological reconstruction and classification methods with the use of morphological features of the regions of interest to detect brain tumors from brain magnetic resonance (MR) images. The CAD system consists of four stages: the preprocessing, the segmentation, region of interest specification and tumor detection stages. The system is evaluated on REMBRANDT dataset with 497 MR image slices of 10 patients. In the classification stage the performance of CAD has achieved accuracy of 93.36% with Decision Tree Algorithm, 94.89% with Artificial Neural Network (Multilayer Perceptron), 96.93% with K-Nearest Neighbour Algorithm and 96.93% with Meta-Learner (Decorate) Algorithm. These results show that the proposed technique is effective and promising for detecting tumors in brain MR images and enhances the classification process to be more accurate. The using morphological reconstruction method is useful and adaptive than the methods used in other CAD applications.[10]

10-Shubhangi S. Veer, Pradeep M. Patil, Brain Tumor Classification Using Artificial Neural Network On Mri Images, International Journal of Research in Engineering and Technology, 2015

In this paper, an attempt has been made to summarize the multi-resolution transformation and the different classifiers useful to analyze the brain tumor using MRI. X-ray, MRI, Ultrasound etc. are different techniques used to scan brain tumor images.

Radiologist prefers MRI to get detail information about tumor to help him diagnoses. In this paper we have used MRI of brain tumor for analysis. We have used Digital image processing tool for detection of the tumor. The identification, detection and classification of brain tumor have been done by extracting features from MRI with the help of wavelet transformation. The MRI of brain tumor is classified into two categories normal and abnormal brain. In this work

Digital image processing has been used as a tool for getting clear and exact details about tumor in earlier stages. This helps the physicians and practitioners for diagnoses.[11]

11-Selvaraj Damodharan and Dhanasekaran R, Combining Tissue Segmentation and Neural Network for Brain Tumor Detection, the International Arab Journal of Information Technology, 2015.

The decisive plan in a large number of image processing applications is to take out the significant features from image data, in which a description, interpretation, or understanding of the scene can be provided by the machine. The segmentation of brain tumor from Magnetic Resonance (MR) images is a vital, but time-consuming task performed by medical experts. In this paper, we have presented an effective brain tumor detection technique based on Neural Network (NN) and our previously designed brain tissue segmentation. This technique hits the target with the aid of the following major steps, which includes: Pre-processing of the brain images., segmentation of pathological tissues (Tumor), normal tissues (White Matter (WM) and Gray Matter (GM)) and fluid (Cerebrospinal Fluid (CSF)), extraction of the relevant features from each segmented tissues and classification of the tumor images with NN. As well, the experimental results and analysis is evaluated by means of Quality Rate (QR) with normal and the abnormal Magnetic Resonance Imaging (MRI) images. The performance of the proposed technique is been validated and compared with the standard evaluation metrics such as sensitivity, specificity and accuracy values for NN, K-NN classification and bayesian classification techniques. The obtained results depicts that the classification results yields better results in NNs when compared with the other techniques.[12]

12- A. Shenbagarajan, V. Ramalingam and S. Palanivel, Tumor Diagnosis in MRI Brain Image Using ACM Segmentation and ANN – LM Classification Techniques, Indian Journal of Science and Technology, 2016.

The results revealed that the proposed MRI brain image tumour diagnosis process is accurate, fast and robust. The classifier based MRI brain image processing approach produced the best MRI brain image classification with use of feature extraction and segmentation results, in terms of accuracy. Best overall classification accuracy results were obtained using the given DioCom Images; The performance results proven that there is not sufficient result given to the classification process when it perform separately. With the use of ACM segmentation and feature extraction approaches, the proposed LM classification approach provides better classification accuracy than the existing approach. Application: The proposed MRI image based brain tumour analysis would efficiently deal with segmentation and classification process for brain tumour analysis with use of feature extraction methods, so this method can yield the better result of brain tumour diagnosis in advance where this method using in medical fields.[13]

Table 2.3 literature review summary

Author/Date	Classification	Objective	Result
Detection and Classification of Brain Tumor using BPN and PNN Artificial Neural Network Algorithms (2015).[3]	1- Back Propagation. 2- Probabilistic.	detected tumourat its early stage	79.02% 97.25%
Brain Tumor Detection and Classification in Magnetic Resonance Imaging (MRI) using Region Growing, Fuzzy Symmetric Measure, and Artificial Neural Network Back propagation (2016).[7]	1- Back Propagation.	Design a system of Computer- Aided Diagnostic (CAD) that will help radiologist in identifying brain tumors.	89.72%
Computer Based Diagnosis System for Tumor Detection &Classification: A Hybrid Approach, (2018).[8]	1-Feed Forward Back-propagation.	Use of Computer Aided Diagnosis Systems (CAD Systems) in the diagnosis of brain tumors.	92.56%

A NovelApproach For Brain Tumor Detection Using Neural Networks, (2015).[9]	1- Feed Forward Back-propagation.	Design a technique for computer-aided detection system for automatic detection of brain tumor	90%
Computer Aided Detection Of Brain Tuomers Using Morphological, (2016).[10]	1- Multilayer Perceptron.	Use a CAD system to reducing the human error in detection process.	94.89%
Brain Tumor Classification Using Artificial Neural Network On Images, (2015).[11]	1- Multilayer Perceptron.	Uses of multi-resolution transformation to analyze the brain tumor.	90%
Combining Tissue Segmentation and Neural Network for Brain Tumor Detection, (2015).[12]	1-KNN. 2- Feed forward Neural Network. 3-Bayesian.	Time-consuming task performed by medicalexperts. so presented an effective brain tumor detection	67% 83% 67%
Tumor Diagnosis in MRI Brain Image Using ACM Segmentation and ANN – LM Classification Techniques, (2016).[13]	1-Levenberg-Marquardt.	System produced the best MRI brain imageclassification with use of feature extraction and segmentation results, in terms of accuracy.	91.14%

In consideration with advantages and disadvantages of the above mentioned methods, this proposed method is a collection of region based, edge based and texture based methods for detection and classification of brain tumors from the MR Images. In the proposed method, it begins with preprocessing of the input images by median filter to highlight the quality of input image. Segmentation was carried using morphological segmentation, that based on morphological opening and closing which solve the problem of the over segmentation and introduce the notion of markers of the objects to be segmented in the image for separating the region of interest (ROI) from MR Images. Then Texture features were extracted from ROI using Gray Level Co-occurrence Matrix (GLCM) feature extraction method. Finally,
the extracted features were fed to three Artificial Neural Network (ANN) classifier Feed forward network, Cascade feed forward and Learning vector quantization to classify the given image into normal or low grade glioma tumor or meningioma tumor.

Chapter Three
Theoretical Background

3.1 Digital Image Processing

An image may be defined as a two-dimensional function, f(x, y) , where x and y are spatial (plane) coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When x, y, and the intensity values of f are all finite, discrete quantities, we call the image a digital image. The field of digital image processing refers to processing digital images by means of a digital computer. Note that a digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are called picture elements, image elements, pels, and pixels. Pixel is the term used most widely to denote the elements of a digital image. [14]

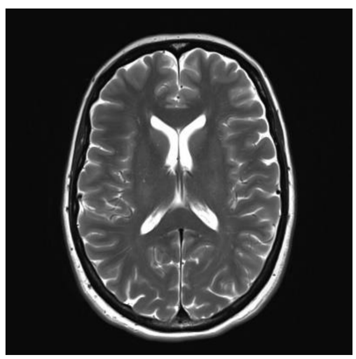

Figure 3- 1 A digital image.[15]

3.2 Sources of Digital Images

The principal source for the images is the electromagnetic (EM) energy spectrum, The spectral bands are grouped according to energy per photon ranging from the gamma rays (highest energy) to the radio waves (lowest energy).

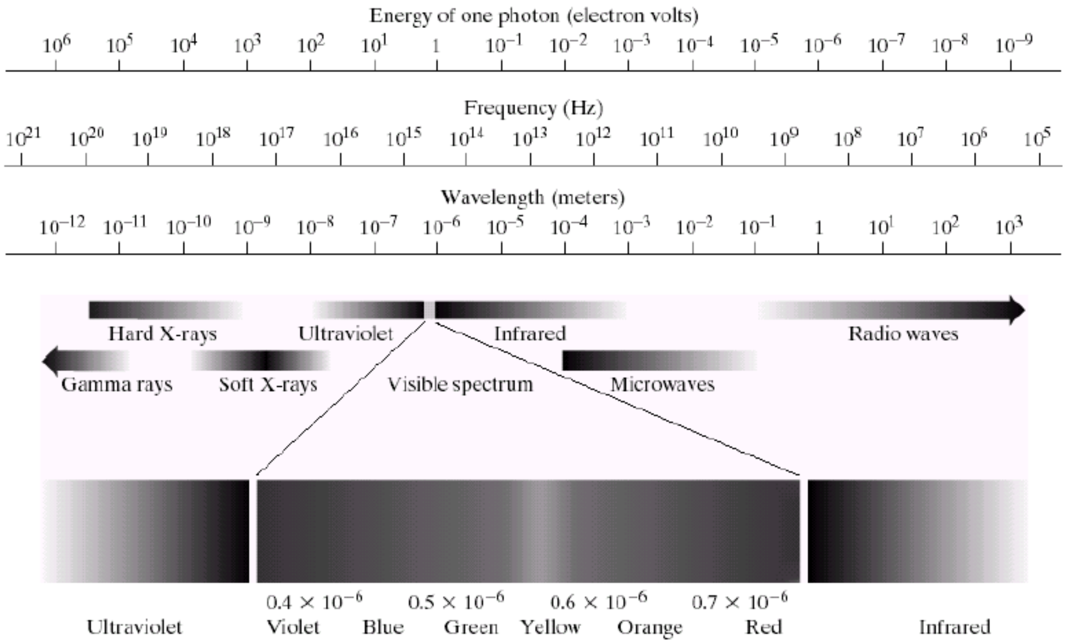

Figure 3- 2The electromagnetic spectrum.[14]

3.3 The fundamental steps of digital image processing

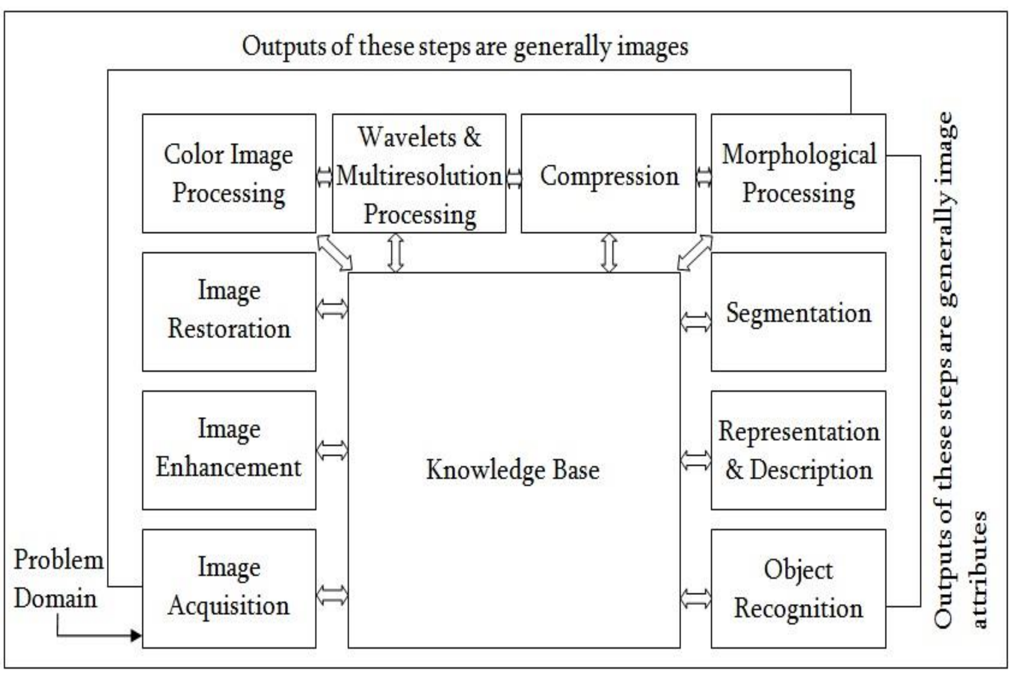

Figure 3- 3Fundamental steps in digital image processing.[15]

3.3.1 Image Acquisition

This is the first step or process of the fundamental steps of digital image processing. Image acquisition could be as simple as being given an image that is already in digital form. Generally, the image acquisition stage involves preprocessing, such as scaling etc.

3.3.2 Image Enhancement

Image enhancement is among the simplest and most appealing areas of digital image processing. Basically, the idea behind enhancement techniques is to bring out detail that is obscured, or simply to highlight certain features of interest in an image. Such as, changing brightness & contrast etc.

3.3.3 Image Restoration

Image restoration is an area that also deals with improving the appearance of an image. However, unlike enhancement, which is subjective, image restoration is objective, in the sense that restoration techniques tend to be based on mathematical or probabilistic models of image degradation.

3.3.4 Color Image Processing

Color image processing is an area that has been gaining its importance because of the significant increase in the use of digital images over the Internet. This may include color modeling and processing in a digital domain etc.

3.3.5 Wavelets and Multi-resolution Processing

Wavelets are the foundation for representing images in various degrees of resolution. Images subdivision successively into smaller regions for data compression and for pyramidal representation.

3.3.6 Compression

Compression deals with techniques for reducing the storage required to save an image or the bandwidth to transmit it. Particularly in the uses of internet it is very much necessary to compress data.

3.3.7 Morphological Processing

Morphological processing deals with tools for extracting image components that are useful in the representation and description of shape.

3.3.8 Segmentation

Segmentation procedures partition an image into its constituent parts or objects. In general, autonomous segmentation is one of the most difficult tasks in digital image processing. A rugged segmentation procedure brings the process a long way toward successful solution of imaging problems that require objects to be identified individually.

3.3.9 Representation and Description

Representation and description almost always follow the output of a segmentation stage, which usually is raw pixel data, constituting either the boundary of a region or all the points in the region itself. Choosing a representation is only part of the solution for transforming raw data into a form suitable for subsequent computer processing. Description deals with extracting attributes that result in some quantitative information of interest or are basic for differentiating one class of objects from another.

3.3.10 Object recognition

Recognition is the process that assigns a label, such as, "vehicle" to an object based on its descriptors.

3.3.11 Knowledge Base

Knowledge may be as simple as detailing regions of an image where the information of interest is known to be located, thus limiting the search that has to be conducted in seeking that information. The knowledge base also can be quite complex, such as an interrelated list of all major possible defects in a materials inspection problem or an image database containing high-resolution satellite images of a region in connection with change-detection applications.[16]

3.4 Median Filter

Median filter is a nonlinear digital filtering technique, used to remove noise from an image or signal. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise.

The median filter works by moving through the image pixel by pixel, Replacing each value with the median value of neighboring pixels. The pattern of neighbors is called the "window", which slides, pixel by pixel over the entire image pixel, image. The median is calculated by first sorting all the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle (median) pixel value.

3.5 Image Formatting

Image file formatsare standardized means of organizing and storing digital images. Image files are composed of digital data in one of these formats that can be rasterized for use on a computer display or printer. An image file format may store data in uncompressed, compressed, or vector formats. Once rasterized, an image becomes a grid of pixels, each of which has a number of bits to designate its color equal to the color depth of the device displaying it.[17]

Table 4.1 Comparison of the main image formats. [17]

Extension	Acronym	Description	Advantages	Disadvantages
BMP	Widows Bit. Map	Handles graphics file within the Microsoft OS.	Wide acceptance, and use in windows programs.	BMP files are large (uncompressed).
GIF	Graphics Interchange Format	Support 256 colors. Widely used to provide image animation effects.	Supports animation.	Limited to 256 colors; no real role compared to other formats.
JPEG	Joint Photographic Experts Group	Supports 8 bits by color, for 24-bit total; habitually lossy.	Small files.	
PNG	Potable Network Graphics	Supports true color (16 million colors); Best suited for editing pictures; Lossless.	Excels when the image has large, uniformly colored areas; Robust.	Many older browsers currently do not support the PNG file format.
RAW	N.A	Family of row image formats; available on some digital cameras		Not standardized\ documented; differ among camera manufactures.

TIFF	Tagged Image File Format	Norrmaly saves 8 or 16 bits per color; lossy; lossless.	Widely accepted as a photograph file standard	Not well supported by web browsers

4.6 Feature Extraction

Texture features or more precisely, Gray Level Co-occurrence Matrix (GLCM) features are used to distinguish between normal and abnormal brain tumors. Five co-occurrence matrices are constructed in four spatial orientations horizontal, right diagonal, vertical and left diagonal A fifth matrix is constructed as the mean of the preceding four matrices, From the mean co-occurrence matrix obtained, these features are as follow. [2]

Table 3.2 Feature extraction equation. [18]

Feature	Equation
Autocorrelation	$\sum i = 1N \sum j = 1N(i * j)P(i.j)$
Cluster Prominence	$\sum i = 1N \sum j = 1N(i + j - 2\mu)3P(i.j)$
Cluster Shade	$\sum i = 1N \sum j = 1N(i + j - 2\mu)4P(i.j)$
Contrast	$\sum i = 1N \sum j = 1N(i - j)2P(i.j)$
Correlation	$\sum i = 1N \sum j = 1N(i * j)P(i.j) - \mu x\mu y\sigma x\sigma y$
Difference Entropy	$-\sum k = 0N - 1px - y(k)logpx - y(k)$

Difference Variance	$\sum k = 0N - 1(k - \mu x - y)2px - y(k)$
Dissimilarity	$\sum i = 1N \sum j = 1N\|i - j\| * P(i.j)$
Energy	$\sum i = 1N \sum j = 1NP(i.j)\ 2$
Entropy	$-\sum i = 1N \sum j = 1NP(i.j)\ logp(i.j)$
Homogeneity	$\sum i = 1N \sum j = 1NP(i.j)\ 1 + (i - j)2$
Information Measure of Correlation 1	HXY-HXY1max(HX,HX)
Information Measure of Correlation 2	1-exp[-2(HXY2-HXY)]
Inverse Difference	$\sum i = 1N \sum j = 1NP(i.j)\ 1 + \|i - j\|$
Maximum Probability	Maxi.jp(i.j)
Sum Average	$\sum k = 22Nkpx + y(k)$
Sum Entropy	$-\sum k = 22Nkpx + y(k)logpx + y(k)$
Sum of Squares	$\sum i = 1N \sum j = 1N(i - \mu)\ 2p(i.j)$
Sum Variance	$\sum k = 22N(k - \mu x + y)2px + y(k)$

3.7 MATLAB

MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. Typical uses include:

1. Math and computation.
2. Algorithm development.
3. Modeling, simulation, and prototyping.
4. Data analysis, exploration, and visualization.
5. Scientific and engineering graphics.
6. Application development, including Graphical User Interface building

MATLAB is an interactive system whose basic data element is an array that does not require dimensioning. This allows you to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time it would take to write a program in a scalar non-interactive language such as C or Fortran.

The name MATLAB stands for matrix laboratory. MATLAB was originally written to provide easy access to matrix software developed by the LINPACK and EISPACK projects, which together represent the state-of-the-art in software for matrix computation.

MATLAB has evolved over a period of years with input from many users. In university environments, it is the standard instructional tool for introductory and advanced courses in mathematics, engineering, and science. In industry, MATLAB is the tool of choice for high-productivity research, development, and analysis.

MATLAB features a family of application-specific solutions called toolboxes. Very important to most users of MATLAB, toolboxes allow you to learn and apply specialized technology. Toolboxes are comprehensive collections of MATLAB functions (M-files) that extend the MATLAB environment to solve particular classes of problems. Areas in which toolboxes are available include signal processing, control systems, neural networks, fuzzy logic, wavelets, simulation, and many others.

3.8 MATLAB language

This is a high-level matrix/array language with control flow statements, functions, data structures, input/output, and object-oriented programming features. It allows both "programming in the small" to rapidly create quick and dirty throw-away programs, and "programming in the large" to create complete large and complex application programs.[19]

3.9 Brain tumor

The brain is the body organ composed of nerve cells and supportive tissues like glial cells and meninges – there are three major parts – they control activity like breathing (brain stem), activity like moving muscles to walk (cerebellum) and senses like sight and our memory, emotions, thinking and personality (cerebrum).

Primary brain tumors can be either malignant (contain cancer cells) or benign (do not contain cancer cells). A primary brain tumor is a tumor which begins in the brain tissue. If a cancerous tumor starts elsewhere in the body, it can spread cancer cells, which grow in the brain. These type of tumors are called secondary or metastatic brain tumors.

Brain tumors can occur at any age. Researchers and doctors do not know exact cause of brain tumors. Risk factors include exposure to ionizing radiation and family history of brain tumors.

The signs symptoms of brain tumors depend on their size, type, and location. The most common signs symptoms include headaches; numbness or tingling in the arms or legs; seizures; memory problems; mood and personality changes; balance and walking problems; nausea and vomiting; or changes in speech, vision, or hearing.

Doctors group brain tumors are classified by grade (grade I, grade II, grade III, or grade IV -the most severe). The grade is determined by the way the cells look under a microscope. The higher the grade number, the more abnormal the cells appear, and the more aggressively the tumor usually behaves.

Diagnosis of a brain tumor is done by a neurologic exam (by a neurologist or neurosurgeon), CT (computer tomography scan) and/or magnetic resonance imaging (MRI), and other tests like an angiogram, spinal tap and biopsy. Your diagnosis helps predict the treatment.[20]

3.9.1 Low Grade Glioma

Low grade gliomas are brain tumors that come from two different types of brain cells known as astrocytes and oligodendrocytes. They are classified as a grade 2 tumor making them the slowest growing type of glioma in adults.

3.9.1.1Symptom of Low Grade Glioma

The most common symptom caused by low grade gliomas are seizures. These can be small seizures that you barely notice, resulting in unusual smells, funny feelings in your stomach or brief spells that you can't explain. Low grade gliomas can also result in larger seizures that affect your ability to talk or lead to shaking movements of your arms and legs. Other symptoms that we can see are headaches, problems with speaking or understanding, personality changes, memory difficulty, numbness, weakness, and vision problems. Like other brain tumors, low grade gliomas cause symptoms depending on what part of the brain they are located in. The brain has specialized areas that help us control speech, sensation, movement, memory, vision, and many other functions. For example, if a brain tumor grows in the part of the brain that controls the right leg, you may have weakness or numbness in that leg. It might also give you seizures that involve the right leg. If you have a tumor in the part of the brain that controls language, you may have trouble speaking or understanding. Most tumors are found because they cause a symptom that leads your doctors to check an MRI or CT of the brain. Sometimes, a patient does not have any symptoms, and the tumor is found when a MRI or CT is done for other reasons.[21]

3.9.1.2 MRI Appearance of low grade glioma

A low grade glioma or astrocytoma may show only a low density area (dark area) whereas high grade gliomas (Glioblastoma) usually show more contrast enhancement (white on the outside) and necrosis in the middle (looks black on the MRI) as shown in the two images below. [22]

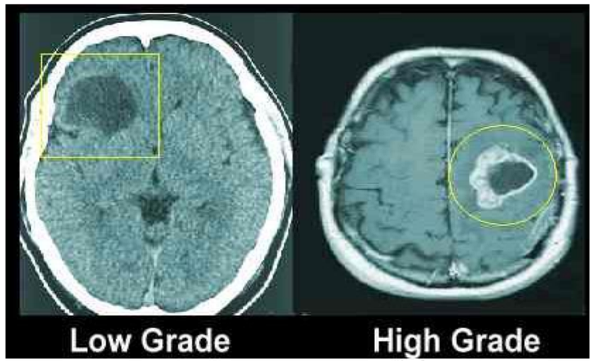

Figure 3.4 Low and high grade glioma appearance in MRI.[22]

3.9.2 Meningioma

Meningioma arise from the meninges, the layer of cells that cover the brain and spinal cord, and account for approximately 30% of all brain tumors. 85% of meningioma represent a benign, non-cancerous tumor. However, in rare cases, they can degenerate into a cancer.

3.9.2.1Symptom of Meningioma

Meningioma compress parts of the brain or spinal cord as they grow, often achieving great size before they put enough pressure on the brain or spine to cause any symptoms at all. Most often, meningiomaare found incidentally on MRIs. If symptoms do present, they generally appear slowly and may be slight at the onset.

Typical symptoms a patient might notice include:

- Headache
- Seizure
- Visual loss
- Loss of sense of smell
- Loss of hearing
- Loss of coordination

In spinal meningioma, difficulty walking and clumsiness in the hands will typically be among the first things patients notice. Very rarely, a large tumor can cause a stroke.[21]

3.9.2.2MRI Appearance of meningioma

Typical appearance of meningioma

T1-weighted non enhanced MRI image shows a (rarely hyper intense) homogeneous, hypo intense round mass with thin capsule.

T2-weighted MRI image shows an isointense and inhomogeneous mass with peripheral edema indicating a more fibrous and harder character

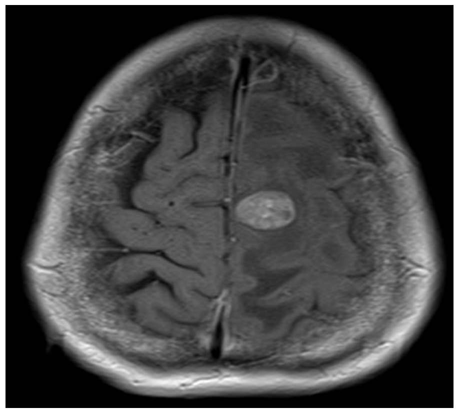

Figure 3.5 Meningioma appearance in MRI. [23]

3.10 Brain tumor grades

The grade of a tumor refers to the way the cells look under a microscope:

Table 3.1 World health organization grading system.[20]

Grade I tumor	• Benign=non-cancerous • Slow growing • Cells look almost normal under a microscope • Usually associated with long-term survival • Rare in adults

Grade II tumor	• Relative slow growing • Sometimes spread to nearby normal tissue and comes back (recurs) • Cell look slightly abnormal under a microscope • Sometimes come back as a higher grade tumor
Grade III tumor	• Malignant=cancerous • Actively reproduces abnormal cells • Tumor spreads into nearby normal parts of the brain • Cell look abnormal under a microscope • Tend to come back, often as a higher grade tumor
Grade IV tumor	• Most malignant • Grows fast • Easily spreads into nearby normal parts of the brain • Actively reproduce abnormal cells • Cells look very abnormal under microscope • Tumor have areas of dead cells in their center (called necrosis)

3.11 Magnetic resonance image

MRI is a non-invasive imaging technology that produces three dimensional detailed anatomical images without the use of damaging radiation. It is often used for disease detection, diagnosis, and treatment monitoring. It is based on sophisticated technology that excites and detects the change in the direction of the rotational axis of protons found in the water that makes up living tissues.

Figure 3.6MRI machine.[24]

3.12 How does MRI work

MRIs employ powerful magnets which produce a strong magnetic field that forces protons in the body to align with that field. When a radiofrequency current is then pulsed through the patient, the protons are stimulated, and spin out of equilibrium, straining against the pull of the magnetic field. When the radiofrequency field is turned off, the MRI sensors are able to detect the energy released as the protons realign with the magnetic field. The time it takes for the protons to realign with the magnetic field, as well as the amount of energy released, changes depending on the environment and the chemical nature of the molecules. Physicians are able to tell the difference between various types of tissues based on these magnetic properties.

To obtain an MRI image, a patient is placed inside a large magnet and must remain very still during the imaging process in order not to blur the image. Contrast agents (often containing the element Gadolinium) may be given to a patient intravenously before or during the MRI to increase the speed at which protons realign with the magnetic field. The faster the protons realign, the brighter the image.

3.13 MRI used for

MRI scanners are particularly well suited to image the non-bony parts or soft tissues of the body. They differ from computed tomography (CT), in that they do not use the damaging ionizing radiation of x-rays. The brain, spinal cord and nerves, as well as muscles, ligaments, and tendons are seen much more clearly with MRI than with regular x-rays and CT; for this reason MRI is often used to image knee and shoulder injuries.

In the brain, MRI can differentiate between white matter and grey matter and can also be used to diagnose aneurysms and tumors. Because MRI does not use x-rays or other radiation, it is the imaging modality of choice when frequent imaging is required for diagnosis or therapy, especially in the brain. However, MRI is more expensive than x-ray imaging or CT scanning.[24]

3.14 Protocol for Routine MRI of the Brain:

Imaging protocols for the brain should meet several criteria:

• They must address the clinical questions to be answered

• They must be complete and provide all the required information

• They must be as short as possible (to minimize the time the patient has to spend in the magnet and optimize patient throughput)

• They must be reproducible Protocols should be standardized to ensure continuity over time. Frequent changes in imaging protocols should be avoided, since this may confuse the technologists operating the MRI equipment. Obviously, imaging protocols should be adapted to the equipment available. As a general rule, MRI studies of the brain should include at least two imaging planes and two "weightings," and preferably more. figure 3.7 provides an overview of (some) standard sequences for MRI of the brain.[25]

3.15 Artificial neural network.

An Artificial Neural Network (ANN) is a mathematical model that tries to simulate the structure and functionalities of biological neural networks. Basic building block of every artificial neural network is artificial neuron, that is, a simple mathematical model (function). Such a model has three simple sets of rules: multiplication, summation and activation. At the entrance of artificial neuron the inputs are weighted what means that every input value is multiplied with individual weight. In the middle section of artificial neuron is sum function that sums all weighted inputs and bias. At the exit of artificial neuron the sum of previously weighted inputs and bias is passing through activation function that is also called transfer function Fig.3.8.

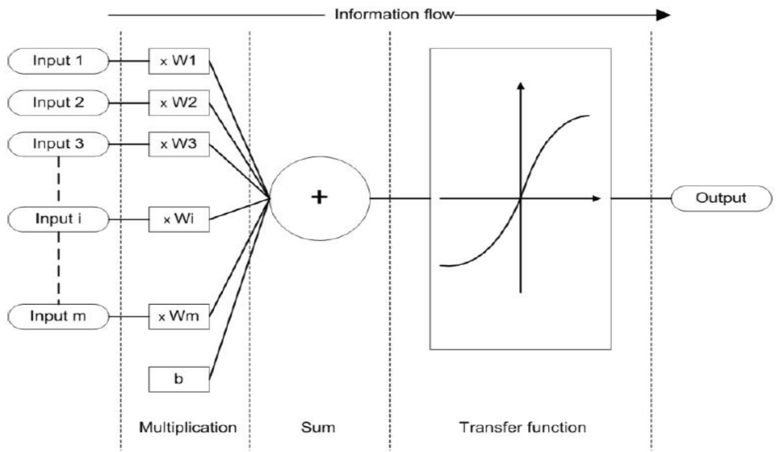

Figure 3.7Working principle of an artificial neuron.[26]

Although the working principles and simple set of rules of artificial neuron looks like nothing special the full potential and calculation power of these models come to life when we start to interconnect them into artificial neural networks Fig 3.21 These artificial neural networks use simple fact that complexity can grow out of merely few basic and simple rules.

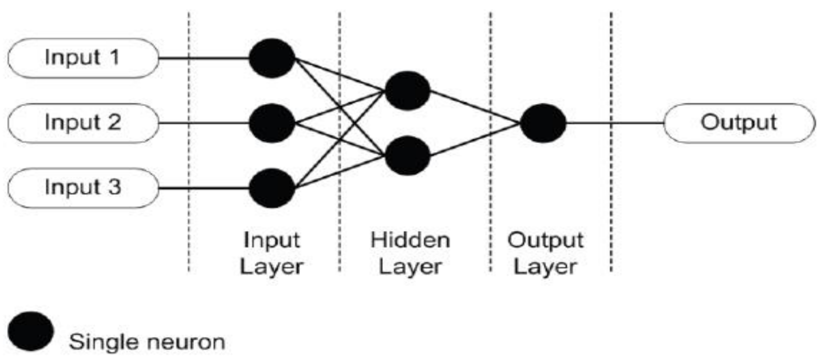

Figure 3.8Example of simple artificial neural network.[21]

3.15.1 Feed-forward Artificial Neural Networks

Artificial neural network with feed-forward topology is called Feed-Forward artificial neural network and as such has only one condition: information must flow from input to output in only one direction with no back-loops. There are no limitations on number of layers, type of transfer function used in individual artificial neuron or number of connections between individual artificial neurons. The simplest feed-forward artificial neural network is a single perceptron that is only capable of learning learning separable problems. Simple multi-layer feed-forward artificial neural network for purpose of analytical description is shown on Fig 3.22.

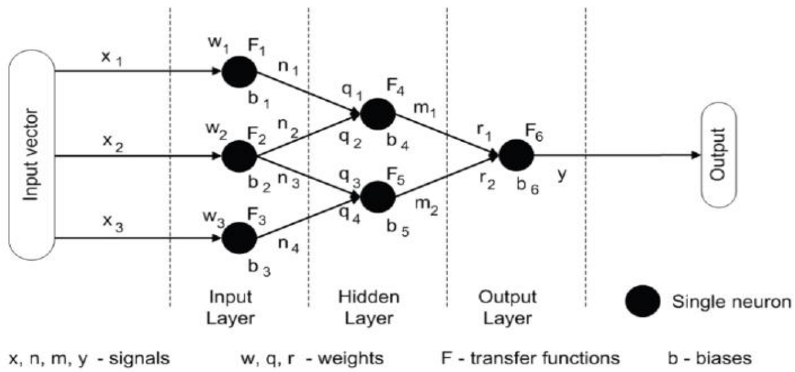

Figure 3.9Feed-forward artificial neural network. **[26]**

3.15.2Cascade Forward Network

Cascade forward back propagation model shown in Fig.2 is similar to feed-forward networks, but include a weight connection from the input to each layer and from each layer to the successive layers. While two-layer feed forward networks can potentially learn virtually any input output relationship, feed-forward networks with more layers might learn complex relationships more quickly.

ANN model is similar to feed forward back propagation neural network in using the back propagation algorithm for weights updating, but the main symptom of this network is that each layer of neurons related to all previous layer of neurons.[27]

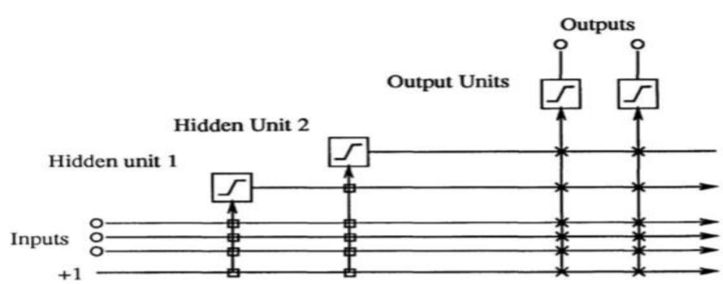

Figure 3.10 Cascade Forward Back Propagation Network.[27]

3.15.3 Learning Vector Quantization

Learning vector quantization (LVQ) is an algorithm that is a type of artificial neural networks and uses neural computation. More broadly, it can be said to be a type of computational intelligence. This algorithm takes a competitive, winner-takes-all approach to learning and is also related to other neural network algorithms like Perceptron and back-propagation. The LVQ algorithm allows one to choose the number of training instances to undergo and then learns about what those instances look like. LVQ was invented by TeuvoKohonen and is related to the k-nearest neighbor algorithm.[27]

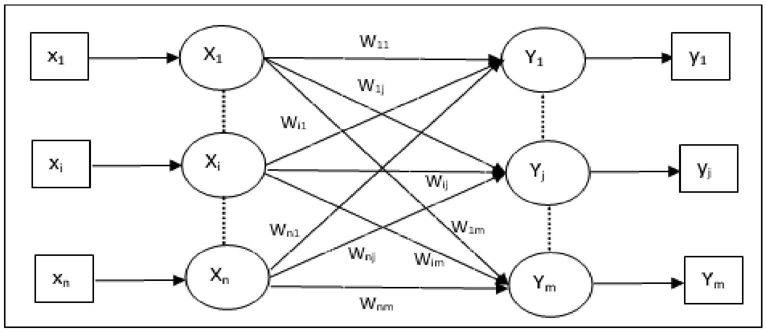

Figure 3.11 Learning vector quantization network.[27]

3.16 Learning

There are three major learning paradigms; supervised learning and unsupervised learning. Usually they can be employed by any given type of artificial neural network architecture. Each learning paradigm has many training algorithms.

3.16.1 Supervised learning

Supervised learning is a machine learning technique that sets parameters of an artificial neural network from training data. The task of the learning artificial neural network is to set the value of its parameters for any valid input value after having seen output value. The training data consist of pairs of input and desired output values that are traditionally represented in data vectors. Supervised learning can also be referred as classification, where we have a wide range of classifiers, each with its strengths and weaknesses. Choosing a suitable classifier (Multilayer perceptron, Support Vector Machines, k-nearest neighbor algorithm, Gaussian mixture model, Gaussian, naive Bayes, decision tree, radial basis function classifiers,…) for a given problem is however still more an art than a science. In order to solve a given problem of supervised learning various steps has to be considered. In the first step we have to determine the type of training examples. In the second step we need to gather a training data set that satisfactory describe a given problem. In the third step we need to describe gathered training data set in form understandable to a chosen artificial neural network. In the fourth step we do the learning and after the learning we can test the performance of learned artificial neural network with the test (validation) data set. Test dataset consist of data that has not been introduced to artificial neural network while learning.

3.16.2 Unsupervised learning

Unsupervised learning is a machine learning technique that sets parameters of an artificial neural network based on given data and a cost function which is to be minimized. Cost function can be any function and it is determined by the task formulation. Unsupervised learning is mostly used in applications that fall within the domain of estimation problems such as statistical modeling, compression, filtering, blind source separation and clustering.

In unsupervised learning we seek to determine how the data is organized. It differs from supervised learning and reinforcement learning in that the artificial neural network is given only unlabeled examples. One common form of unsupervised learning is clustering where we try to categorize data in different clusters by their similarity. Among above described artificial neural network models, the Self-organizing maps are the ones that the most commonly use unsupervised learning algorithms.[21]

Chapter Four

Methodology (Proposed System)

4.1 System overview

In the course of achieving the proposed objectives of this research, the algorithm implementation mainly comprises of the capabilities of MATLAB Toolboxes. Software program was created for the purpose of performing image processing and enhancement and classification on raw MR images.

The MR images of brain used in this project are provided by hospitals. The dataset consist of digitized brain images that composes of brain .each of these images are marked by expert radiologists.

This project was divided into four main phases: Data Collection, Image Processing, Image Segmentation, Feature Extraction and Neural Network Classifier.

4.2 Data Collection

All MRI scan images of brain that used on this project were collected from Harvard citations [28]cancer imaging archive[29] and figshare[30]from were found the web of science database. The database consists of 43 images of normal brain and 300 images with brain tumor.

4.3 Image Processing

Image processing procedures play most crucial part for the project. The original images in the GIF format, the first step is transfer the images into JPEG format, and then the median filter is used.

Median filtering is a nonlearning method used to remove noise from images. It is widely used as it is very effective at removing noise while preserving edges. The median filter works by moving through the image pixel by pixel, Replacing each value with the median value of neighboring pixels. The pattern of neighbors is called the "window", which slides, pixel by pixel over the entire image pixel, image. The median is calculated by first sorting all the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle (median) pixel value.

4.4 Image Segmentation

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super-pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.

Image segmentation is typically used to locate objects and boundaries in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.

A region of interest (ROI) is a subset of an image or a dataset identified for a particular purpose. it can be defined as a portion of an image which is needed to be filtered or to be performed some other operation on.

The segmentation in this thesis is based on morphological segmentation that based on morphological opening and closing which solve the problem of the over segmentation and introduce the notion of markers of the objects to be segmented in the image. [31]

Morphological Dilation and Erosion. Morphology is a broad set of image processing operations that process images based on shapes. Morphological operations apply a structuring element to an input image, creating an output image of the same size.

4.5 Feature Extraction

Texture features or more precisely, Gray Level Co-occurrence Matrix (GLCM) features are used to distinguish between normal and abnormal brain tumors. Five co-occurrence matrices are constructed in four spatial orientations horizontal, right diagonal, vertical and left diagonal A fifth matrix is constructed as the mean of the preceding four matrices, From the mean co-occurrence matrix obtained, we have to extract the 22 different statistical features and these extracted features is applied at input of neural network. These features are as follow. [2]

4.6 Neural Network Classifier

A neural network consists of units (neurons), arranged in layers, which convert an input vector into some output. Each unit takes an input, applies a (often nonlearning) function to it and then passes the output on to the next layer. Generally the networks are defined to be feed-forward: a unit feeds its output to all the units on the next layer, but there is no feedback to the previous layer. Weightings are applied to the signals passing from one unit to another, and it is these weightings which are tuned in the training phase to adapt a neural network to the particular problem at hand.

4.7 Design Graphical User Interface

A graphical user interface (GUI) is a graphical display in one or more windows containing controls, called components that enable a user to perform interactive tasks. The user of the GUI does not have to create a script or type commands at the command line to accomplish the tasks.

A GUIDE, it's the MATLAB Graphical User Interface Development Environment, provides a set of tools for creating graphical user interfaces (GUIs). These tools greatly simplify the process of laying out and programming GUIs. GUIs created using MATLAB tools can also perform any type of computation, read and write data files, communicate with other GUIs, and display data as tables or as plots.[32]

1. Components Each item on a MATLAB GUI (pushbuttons, labels, edit boxes, etc.) is a graphical component. The types of components include graphical controls (pushbuttons, edit boxes, lists, sliders, etc.), static elements (frames and text strings), menus, and axes. Graphical controls and static elements are created by the function control, and menus are created by the functions submenu and context menu. Axes, which are used to display graphical data, are created by the function axes.

2. Figures The components of a GUI must be arranged within a figure, which is a window on the computer screen. In the past, figures have been created automatically whenever we have plotted

data. However, empty figures can be created with the function figure and can be used to hold any combination of components.

3. Call-backs Finally, there must be some way to perform an action if a user clicks a mouse on a button or types information on a keyboard. A mouse click or a key press is an event, and the MATLAB program must respond to each event if the program is to perform its function.

For GUI Development Environment, The process of implementing a GUI involves two basic tasks:

• Laying out the GUI components

• Programming the GUI components

On this research that MATLAB R2016b was used, after GUIDE was selected figure 4.2 was opened and tools were selected.

Chapter Five

Results and Discussion

5.1 Results

With the tumor detection system fully developed using MATLAB, the means to evaluate the efficacy of the methods and algorithms used, is crucial. A total of 343 samples of MRI brain images containing masses have been compiled for this project.

- 150 brain images which contain meningioma cases.
- 150 brain images which contain low grade glioma cases.
- 43 brain images which contain normal cases.

5.1.1 Results for stages

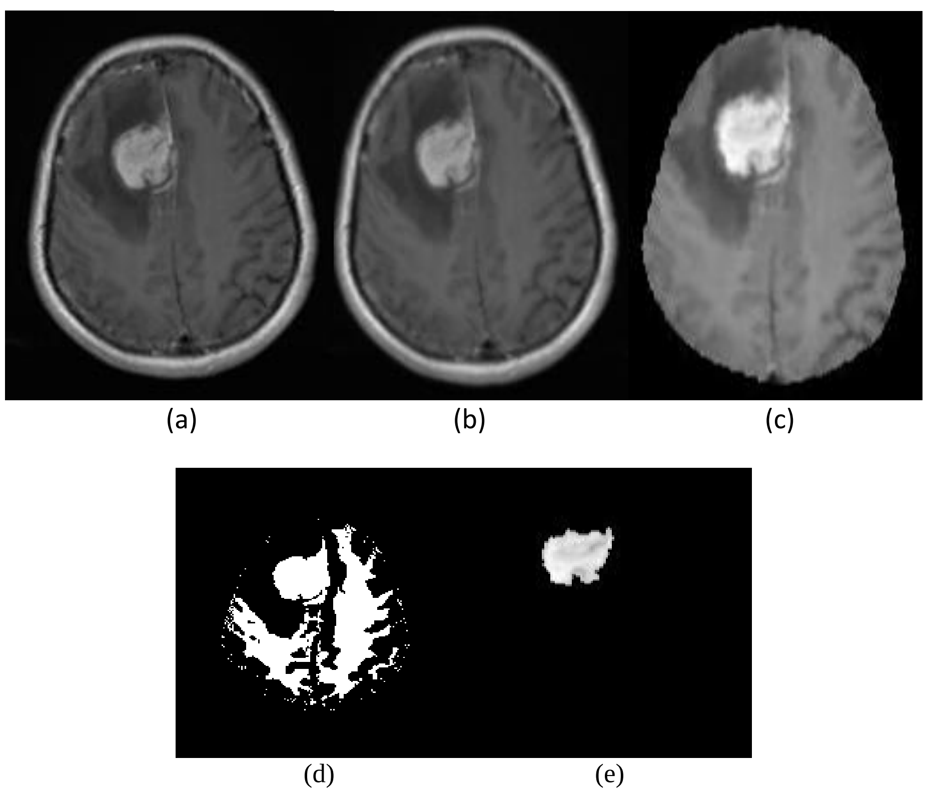

Figure 5- 1 Original Image(a).Filtered Image(b). Skull Removal (c). Binary image (d). Segmented Image(e).

5.2 Result of Graphical User Interface (GUI) of the system

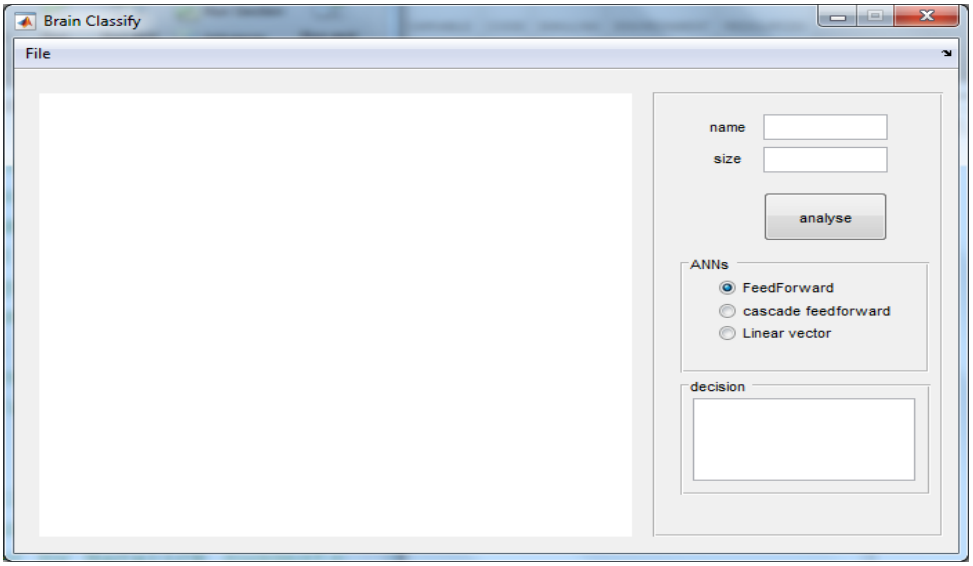

Figure 5.2 GUI window.

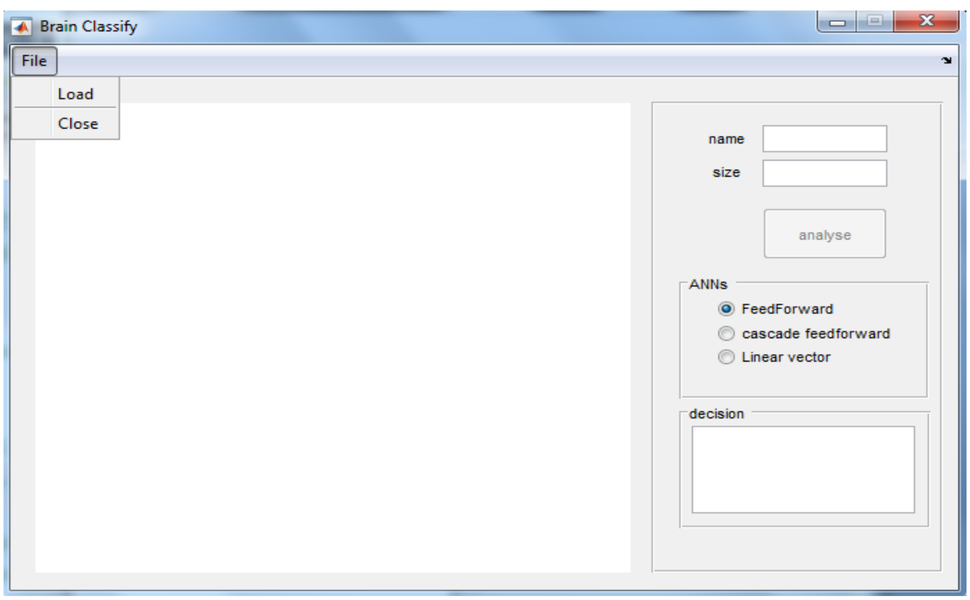

Figure 5.3 File icon for load an image.

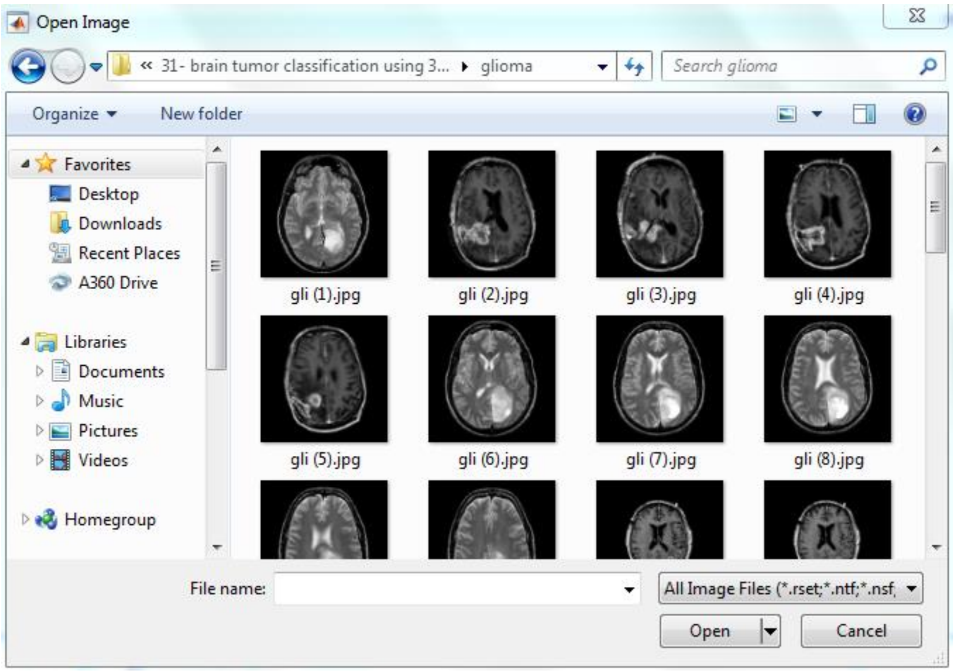

Figure 5.4 Window for loading image to GUI window.

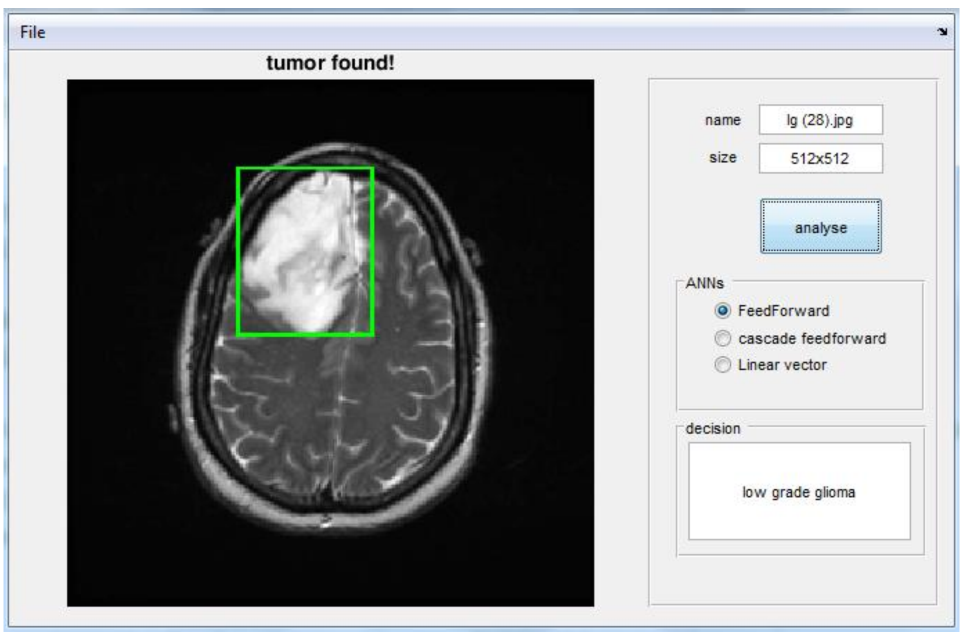

Figure 5- 5 GUI of Tumor diagnosis system with the illustration of low grade glioma mass in Brain image being segmented and classified.

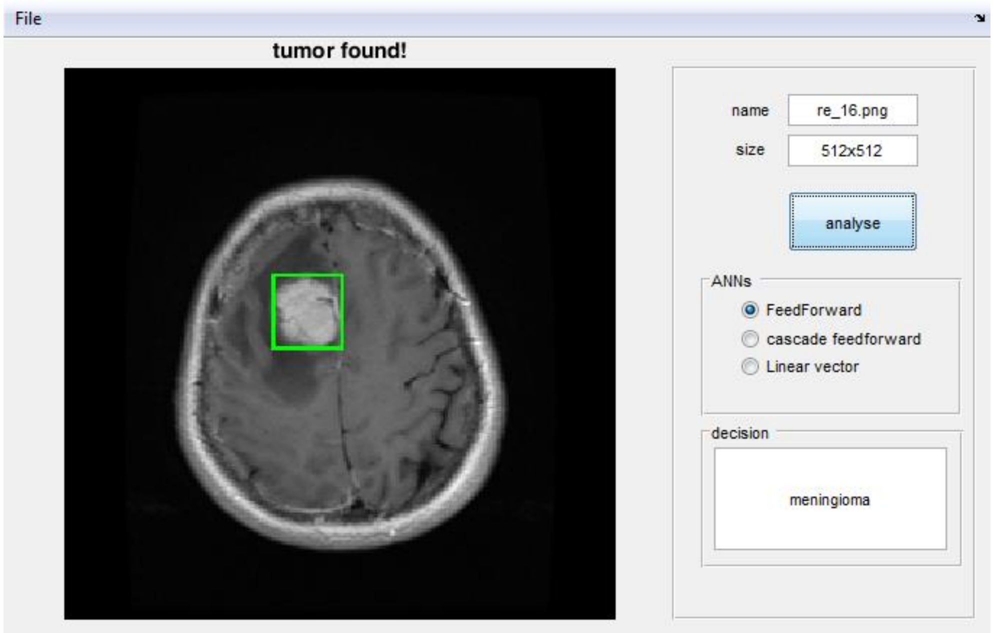

Figure 5- 6 GUI of Tumor diagnosis system with the illustration of meningioma mass in Brain image being segmented and classified.

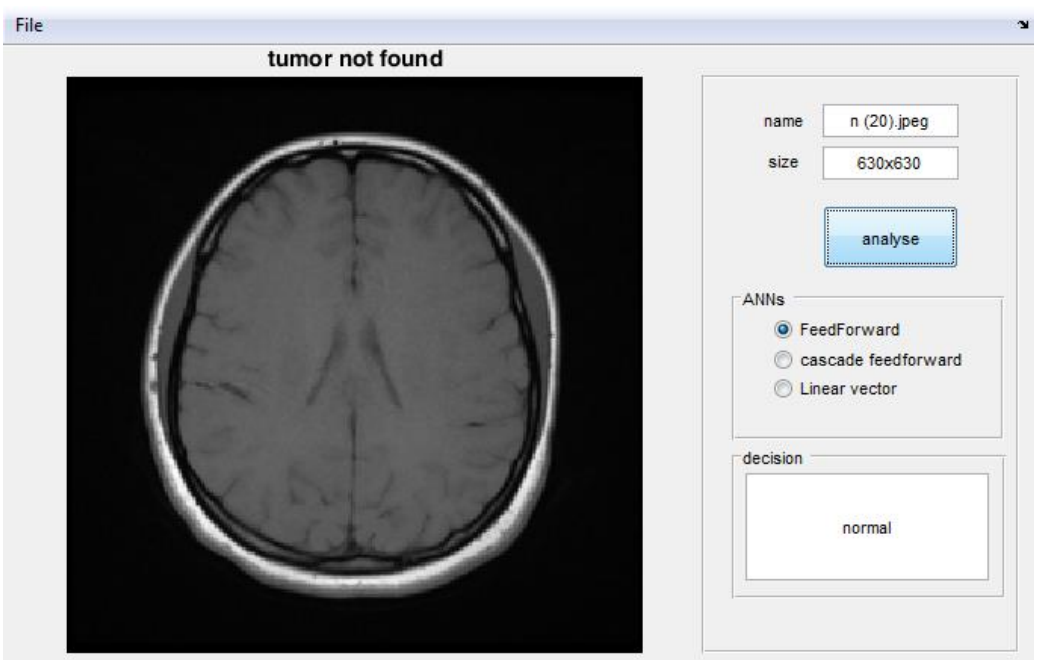

Figure 5- 7 GUI of Tumor diagnosis system with the illustration of normal Brain image being segmented and classified.

5.3 Features Classifications

The features they were extracted from the entire MRI images were classified using Feed Forward Neural Network. And the performance of the Feature dataset in discriminating between normal and abnormal cases images.

Table 5.1 Texture features of four low grade glioma tumors from database

S.NO	Texture Feature	Image 1	Image 2	Image 3	Image 4
1	Autocorrelation	11.480	18.716	13.661	13.681
2	Contrast	0.957	0.694	0.729	0.728
3	Correlation	0.828	0.844	0.848	0.881
4	Cluster Prominence	0.828	0.844	0.848	0.881
5	Cluster Shade	147.436	218.800	145.254	192.004
6	Dissimilarity	-4.678	-32.304	-15.917	-14.207
7	Energy	0.527	0.344	0.395	0.398
8	Entropy	0.150	0.386	0.178	0.194
9	Homogeneity	2.430	1.593	2.179	2.123
10	Homogeneity	0.797	0.874	0.849	0.847
11	Maximum probability	0.780	0.863	0.836	0.834
12	Sum of squares	0.301	0.601	0.270	0.296
13	Sum average	11.897	18.942	13.914	13.919
14	Sum variance	6.058	8.206	6.819	6.630
15	Sum entropy	26.739	54.836	33.491	34.324
16	Difference variance	1.988	1.378	1.857	1.852
17	Difference entropy	0.957	0.694	0.729	0.728
18	Information measure of correlation1	0.967	0.733	0.815	0.822
19	Information measure of correlation2	-0.355	-0.426	-0.444	-0.451
20	Inverse difference (INV) is homom	0.805	0.762	0.844	0.844
21	Inverse difference normalized (INN)	0.946	0.965	0.960	0.959
22	Inverse difference moment normalized	0.986	0.990	0.989	0.990

Table 5.2 Texture features of four meningioma tumors from database

S.NO	Texture Feature	Image 1	Image 2	Image 3	Image 4
1	Autocorrelation	6.141	17.771	14.557	11.420
2	Contrast	0.414	1.234	0.825	0.808
3	Correlation	0.755	0.851	0.880	0.820
4	Cluster Prominence	0.755	0.851	0.880	0.820
5	Cluster Shade	15.319	341.520	219.621	108.462
6	Dissimilarity	-3.750	-22.483	-15.333	-10.581
7	Energy	0.227	0.624	0.430	0.468
8	Entropy	0.428	0.123	0.258	0.180
9	Homogeneity	1.142	2.583	2.007	2.202
10	Homogeneity	0.918	0.766	0.839	0.814
11	Maximum probability	0.905	0.747	0.824	0.800
12	Sum of squares	0.595	0.226	0.426	0.319
13	Sum average	6.326	18.294	14.868	11.711
14	Sum variance	4.691	7.547	6.790	6.192
15	Sum entropy	16.269	45.095	38.728	26.893
16	Difference variance	1.044	2.094	1.713	1.862
17	Difference entropy	0.414	1.234	0.825	0.808
18	Information measure of correlation1	0.466	1.066	0.859	0.904
19	Information measure of correlation2	-0.467	-0.345	-0.442	-0.351
20	Inverse difference (INV) is homom	0.711	0.813	0.825	0.781
21	Inverse difference normalized (INN)	0.977	0.937	0.956	0.952
22	Inverse difference moment normalized	0.994	0.983	0.988	0.988

Table 5.3 Texture features of four normal image from database

S.NO	Texture Feature	Image 1	Image 2	Image 3	Image 4
1	Autocorrelation	7.575	9.161	10.281	16.934
2	Contrast	0.764	1.133	1.296	2.562
3	Correlation	0.825	0.624	0.791	0.797
4	Cluster Prominence	0.825	0.624	0.791	0.797
5	Cluster Shade	117.731	46.948	237.322	927.427
6	Dissimilarity	10.647	-6.680	14.166	48.122

7	Energy	0.488	0.553	0.713	0.961
8	Entropy	0.189	0.185	0.150	0.139
9	Homogeneity	2.339	1.882	2.612	2.938
10	Homogeneity	0.799	0.804	0.728	0.703
11	Maximum probability	0.783	0.781	0.702	0.666
12	Sum of squares	0.400	0.309	0.349	0.350
13	Sum average	7.919	9.508	10.832	18.104
14	Sum variance	4.804	5.735	5.596	6.902
15	Sum entropy	16.274	21.308	23.247	43.585
16	Difference variance	1.925	1.682	2.111	2.327
17	Difference entropy	0.764	1.133	1.296	2.562
18	Information measure of correlation1	0.915	0.964	1.116	1.325
19	Information measure of correlation2	-0.370	-0.258	-0.336	-0.342
20	Inverse difference (INV) is homom	0.810	0.654	0.806	0.838
21	Inverse difference normalized (INN)	0.949	0.945	0.927	0.909
22	Inverse difference moment normalized	0.989	0.984	0.981	0.966

5.3.1 Performance measures

Sensitivity (SE): Is the ratio of abnormal tissue which were marked and

Classified as Tumor, to all marked tissue.

$$\textbf{SE}=\frac{TP}{TP+FN}\quad(5.1)$$

Specificity (SP): Is the ratio of abnormal tissue which were marked and classified as normal brain tissue, to all marked tissue.

$$\textbf{SP}=\frac{TN}{FP+TN}\quad(5.2)$$

Positive Predictive Value (PPV): Is the proportion of abnormal tissue Correctly identified.

$$\textbf{PPV} = \frac{TP}{TP+FP} \quad (5.3)$$

Negative Predictive Value (NPV): Is the proportion of Normal brain tissue case correctly identified.

$$\textbf{NPV} = \frac{TN}{FN+TN} \quad (5.4)$$

Where:

True Positives (TP): brain tissue marked as abnormal tissues which were also classified as brain tumor.

True Negatives (TN): brain tissues which were marked as Normal brain tissues and that were also classified as Normal brain tissues.

False Positives (FP): abnormal tissues which were marked as Normal tissues, but were classified as tumor tissues.

False Negatives (FN): abnormal tissues which were marked as brain tumor tissues, but which were classified as Normal brain tissues.[33]

Table 5-4compare between networks used

Classification	Accuracy	Sensitivity	Specificity	Error Rate
Feed Forward	97.91 %	94.59%	100%	2.08%
Cascade FeedForward	96.88%	95.23%	98.14%	3.13%
Learning Vector Quantization	56.25%	0%	100%	43.75%

Table 5.5 Accuracy Comparison Table of Proposed System with some of Existing Systems.

No	Author	Classification	Accuracy
1	Proposed system	1- Feed Forward 2- Cascade FeedForward 3- Learning Vector Quantization	97.91 % 96.88% 56.25%
2	Lugina Muhammad et.al[7]	1- Back Propagation.	89.72%
3	Virupakshappa et.al[8]	1- Feed Forward Back Propagation.	92.56%
4	Said Charfi et.al[9]	1- Feed Forward Back Propagation.	90%
5	SelvarajDamodharan et.al[12]	1- KNN. 2- Feed Forward. 3- Bayesian	67% 83% 67%
6	Naveena H S et.al[2]	1- Back Propagation. 2- Probabilistic.	79.02% 97.25%

Chapter Six

Conclusions and Recommendations

6.1 Conclusions

This thesis aimed to design automatic algorithm to detect the brain tumor from MRI images by artificial neural networks. This algorithm has been successfully designed. The data collected from Harvard citations, Cancer imaging archiveand Figshare,it's prepared by pre-processing operation to make it suitable to detect.

The proposed system used median filter for preprocessing and morphological segmentation with opening and closing operation was used in segmentation process.

The statistical feature analysis was used to extract features from images; the features computed from equations of Haralick's features based on the spatial Gray-level co-occurrence matrices (GLCM) feature of images.

The study involves three types of ANNs which are Feed forward, Cascade feed forward and learning vector quantizationto determine which one has the best performance for medical image recognition and brain tumor diagnosis.

Result obtained in chapter five explain that the best diagnosis achieved when Feed forward is applied with performance ratio 97.91 %.

The brain tumor detection and classification is successfully implemented by using the image processing tool box , neural network tool box and graphical user interface.

6.2 Recommendations

The following recommendations are suggested:

1. Design auto dynamic brain tumor detection system, detect the tumor according to its size, direction and shape in image.

2. More features that could be added in addition to the Haralick's feature to the system include metabolic and genetic data as well as anatomical attributes of the brain.

3. Develop the proposed algorithm to classify more type of brain tumors.

4. In many cases when Neural Networks combines with other artificial intelligent techniques as in Neuro-Fuzzy system, the performance will become better, Best performance will be achieved when used genetic algorithm with ANNs.

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