بسم الله الرحمن الرحيم

Sudan University of Science and Technology
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Biomedical Engineering Department

Brain Tumor Detection by Using Artificial Neural Networks

الكشف عن أورام الدماغ باستخدام الشبكات العصبية الاصطناعية

A Thesis submitted in partial fulfillment of the requirements for the M.Sc. Degree in Biomedical Engineering

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الآية

قال تعالى :

بسم الله الرحمن الرحيم

"قَالُوا سُبْحَانَكَ لَا عِلْمَ لَنَا إِلَّا مَا عَلَّمْتَنَا إِنَّكَ أَنْتَ الْعَلِيمُ الْحَكِيمُ"

صدق الله العظيم

سورة البقرة الآية رقم 32

DEDICATION

I desire to dedicate this effort to everyone believe in me before I believe in myself,

A special feeling of gratitude to my loving parents Who encourage me to continue and go forward

To the man who is tired of us….. to the one who taught me the success getting by the effort and patience…. to my dear father **Elnoor Mohamed**

To who I am part of them in to taught me the meaning of life to my dear mother **Aisha Mohamed**.

I dedicate this thesis to my sisters and brothers and all my family, have never left my side, and support me to complete this thesis.

Also I can't never forget my friends

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I have taken efforts in this project. However, it would not have been possible without the kind support and help of many individuals, so I would like to extend my sincere thanks **to all staff of Biomedical Engineering department special D. Zeinb Aadam, T. Kwther and T.Fatihya Grmma.**

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ABBREVIATIONS

MRI	Magnetic Resonance Imaging
GUI	Graphic User Interface
CAD	Computer Aided Detection
ANNs	Artificial Neural Networks
SGLD	Spatial Gray Level Dependency
NBTF	The National Brain Tumor Foundation
PEs	Processing Elements
ADC	Analog-to-digital converter
DAC	digital-to-analog converter
CNS	central nervous system

TABLE OF CONTENS

LIST OF FIGURES:

ABSTRACT

Brain tumor is one of the most dangerous diseases which require early and accurately detection methods, current used detection and diagnosis methods for image evaluation depend on decision of neuro-specialists, and radiologist which possible to human errors. Manual classification of brain tumor is time consuming. This study describes the processes and techniques used in detecting brain tumor from magnetic resonance imaging (MRI) and ANN techniques, which are of the most application of artificial intelligent that used in biomedical image classification and recognition.

In the proposed system, features are extracted from raw MRI images which are then fed to ANN through GUI to received suspected MRI for early tumor detection. This thesis implemented in the different stages for Computer Aided Detection System (CAD-system) after collected the image data (magnetic resonance images); first stage is pre-processing and post-processing of MRI images to enhancement it and then the processed image is being more suitable to analysis. The study was used threshold to segment the MRI images by applied mean gray level method. A comprehensive feature set , computed and ANN rules are selected to classify normal and abnormal image.

In the second stage statistical feature analysis was used to extract features from MRI images; the features were computed using Haralick's equation for feature based on the spatial gray level dependency matrix (SGLD).

The suitable and best features to detect the tumor in image were selected. In the third stage the artificial neural networks (ANN) were designed; the feed-forward back propagation neural network with supervised learning were apply as automatic method to classify the images under investigation into tumor or none tumor . The network performances were evaluated successfully tested and achieved best results with accuracy of 99%,specificity100% and sensitivity 97.9%.

المستخلص

أورام الدماغ هي عبارة عن نمو غير طبيعي للخلايا داخل الجمجمة مما يؤدي إلى حدوث أضرار جسيمة وأمراض تهدد الحياة والأسباب التي تؤدي إلي نشوء هذه الأورام غير معروفة.

تعتبر أورام الدماغ من أكثر الأمراض الخطيرة التي تتطلب كشفا مبكر أو تشخيص دقيقا ومعظم الطرق المتبعة في تشخيص هذه الأورام عبارة عن قرار يتخذه أخصائي الأشعة والأورام لتقييم الصور المختصة بالكشف عن الأورام ولكن هذا التشخيص الذي يعتمد على عين الإنسان ومهارته المكتسبة قد يؤدي إلى حدوث أخطاء بشرية و كذالك يحتاج إلى وقت أطول.

الطريقة المستخدمة في هذا البحث للكشف عن ورم في الدماغ تقوم على تقنيات التصوير بالرنين المغناطيسي (MRI) وتقنيات الشبكات العصبية الاصطناعية (ANN)، والتي تمثل واحدة من التطبيقات الاصطناعية الذكية المستخدمة في الطب لتصنيف الصور واتخاذ القرار لها. وهذا المقترح تم تنفيذه بعد تجميع عدد من صور الرنين المغنطيسي في مراحل مختلفة من نظام التشخيص بمساعدة الحاسوب (CAD System). أول مرحلة تمت فيها معالجة الصور لتحسينها وجعلها مناسبة لعملية التحليل وكذلك استخدمت التقسيم ألعتبي (threshold segmentation) لتقسيم الصورة. وفي المرحلة الثانية استخدمت طريقة التحليل ألملمسي الإحصائي (statisitical texure analysis) وتم حساب خصائص الصور باستخدام معادلات هارليك (Haralick's Features) المشتقة من طريقة إحصائية تسمى (Spatial Gray Level Dependancy Matrix) ثم اختيرت أفضل الخصائص والأنسب لتشخيص الورم المتوقع.

,وفي المرحلة الثالثة تم بناء الشبكة العصبية الاصطناعية من نوع (feed-forward back propagation neural network) كطريقة آلية لتشخيص الصور المدخلة للنظام إلى طبيعية وغير طبيعية. وكان تقيم أداء الشبكة عالي النجاح حيث أعطت نتائج بحساسية قيمتها 97.7% ودقة قيمتها 99%.

CHAPTER ONE

INTRODUCTION

CHAPTER ONE
1.INTRODUCTION

1.1 Background

Brain tumor is any mass that results from an abnormal and an uncontrolled growth of cells in the brain. There are two main types of tumors: malignant or cancerous tumors and benign tumors. Cancerous tumors can be divided into primary tumors that started within the brain and those that spread from somewhere else known as brain metastasis tumors .benign tumors generally have a slower growth rate than malignant tumors[1].Its threat level depends on a combination of factors like the type of tumor, its location, its size and its state of development. Brain tumors either include tumors in the central spinal canal or inside the cranium[2].The National Brain Tumor Foundation (NBTF) for research in United States estimates that 29,000 people in the U.S are diagnosed with primary brain tumors each year, and nearly 13,000 people die. In the UK, over 4,200 people are diagnosed with a brain tumor every year (2007 estimates). There are about 200 other types of tumors diagnosed in UK each year[3]. Magnetic Resonance Imaging (MRI) is one of the best technologies currently being used for diagnosing brain tumor and it create more detailed pictures .Automatic defects detection in MRI is quite useful in several diagnostic and therapeutic applications [4, 5]. MRI is one imaging modality that helps researchers and medical practitioners to study the brain by looking at it non-invasively.

With the advances of digital image processing, radiologists have a chance to improve their performance with automatic methods like computer-aided detection (CAD) system and Artificial Neural Networks. Computer-aided diagnosis (CAD) aims to increase the predictive value of the technique by pre-reading medical images to show the locations of suspicious abnormalities, and analyze their characteristics, as an aid to the radiologist[6].

Artificial neural networks are one application of artificial intelligent and it’s a model that emulates a biological neural network. An ANNs is composed of a collection of interconnected neurons that are often grouped in layers .neurons is the processing elements (PEs) in a network. Each neuron receives input data, processing it, and delivers a single output. A neural network is a powerful computational data model that is able to capture and represent complex input/output relationships [7].

And also it is provides a powerful tool to help doctors to analyze, model and make sense of complex clinical data across a broad range of medical applications. Most applications of artificial neural networks to medicine are classification problems such as pattern recognition; that is, the task is on the basis of the measured features to assign the patient to one of a small set of classes [8, 9].

1.2Significance of the study

Brain tumor is one of the most dangerous diseases which require early and precision detection and most of its detection methods depend on decision of neuro-specialists , and radiologist for image evaluation which possible to make misdiagnosis due to human errors and also requires more effort and a long time to detect it.

1.3 Aim of the Study:

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 are:

1. The main purpose is detection brain tumors from magnetic resonance image.
2. Using automatic method to detect the brain tumor by artificial neural network’s to increase the accuracy and yield.
3. Decrease the diagnosis time and support the decision of doctors and radiologist.

4. Find out the extent of artificial neural network's merit in brain tumor detection.

5. Design graphic user interface window(GUI) for detection method.

1.4 Subject and Method:

In this study artificial neural networks (ANNs) were used as diagnosis method for brain tumor detection from magnetic resonance image (MRI). The detection of the tumor is performed in two stages: Preprocessing and enhancement in the first stage and segmentation and classification in the second stage which using different stages of Computer Aided Detection System (CAD) then use statistical method; Haralick's feature extraction which one of texture analysis and the last used this feature as input parameters to the feed-forward back propagation Artificial neural networks which designed by the neural networks toolbox in MATLAB and implemented all the result in graphic user interface window.

1.6Thesis layout:

In this thesis; Chapter one discusses the briefly background, problem statements and thesis objectives, thesis methodology briefly introduced and literature reviews, Chapter two will discuss the related studies; computer aided diagnosis system, digital image processing, feature analysis and literature review, Chapter three discusses the theoretical fundamental include; brain tumor, MRI brain images and artificial neural network, Chapter four discusses and describe the methodology that apply to detect brain tumor from MRI images, Chapter five introduces the obtained results from the proposed system designed and discussions of the analysis results and the last chapter; Chapter six provide the conclusions and recommendations of the thesis.

CHAPTER TWO

RELATED STUDIES

CHAPTER TWO

2.RELATED STUDIES

This chapter discuses an introduction about computer aided diagnosis ,digital image processing, texture analysis and literature review by different methods to detect brain tumor.

2.1Computer-Aided Diagnosis (CAD)System

Computer-aided diagnosis (CAD) is procedure in medicine that assist doctors in the interpretation of medical images. Imaging techniques in X-ray, MRI, and Ultrasound diagnostics yield a great deal of information, which the radiologist has to analyze and evaluate comprehensively in a short time. CAD systems help scan digital images. It is a relatively young interdisciplinary technology combining elements of artificial intelligence and digital image processing with radiological image processing. A typical application is the detection of a tumor.

2.2 Digital Imaging Processing

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing . A complete digital image processing system is a collection of hardware (equipment) and software (computer programs) that can: acquire an image, using appropriate sensors to detect the object, Analog-to-digital converter (ADC) to digitize image, store the image, manipulate, process the image; and display the image, ideally on a television or computer monitor, which requires the production of an analog video display signal by a digital-to-analog converter (DAC).imaging processing consist several processes some of them are segmentation and feature extraction which describe bellow:

2.2.1 Image Segmentation:

Image segmentation is the process of dividing an image into multiple parts. This is typically used to identify objects or other relevant information in digital images. There are many different ways to perform images segmentation[10].there are some categories of image segmentation:

- *Threshold based segmentation.* Its the simplest method of image segmentation. This method is based on a threshold value to turn a gray-scale image into a binary image. Histogram thresholding and slicing techniques are used to segment the image. They may be applied directly to an image, but can also be combined with pre- and post-processing techniques.
- *Edge based segmentation.* With this technique, detected edges in an image are assumed to represent object boundaries, and used to identify these objects.
- *Region based segmentation*. Where an edge based technique may attempt to find the object boundaries and then locate the object itself by fling them in, a region based technique takes the opposite approach, by (e.g.) starting in the middle of an object and then “growing” outward until it meets the object boundaries.
- *Clustering techniques.* Although clustering is sometimes used as a synonym for (agglomerative) segmentation techniques, it used to denote techniques that are primarily used in exploratory data analysis of high-dimensional measurement patterns. Clustering methods attempt to group together patterns that are similar in some sense. This goal is very similar to what we are attempting to do when we segment an image, and indeed some clustering techniques can readily be applied for image segmentation.

- *Matching.* When we know what an object we wish to identify in an image (approximately) looks like, we can use this knowledge to locate the object in an image. This approach to segmentation is called matching.

2.2.2 Feature Extraction

Feature extraction is an essential pre-processing step to pattern recognition and machine learning problems. The problem of feature extraction can be decomposing in two steps: feature construction, and feature selection. Although feature selection is primarily performed to select relevant and informative features, it can have other motivations, including:

- General data reduction, to limit storage requirements and increase algorithm speed.
- Feature set reduction, to save resources in the next round of data collection or during utilization.
- Performance improvement, to gain in predictive accuracy.
- Data understanding, to gain knowledge about the process that generated the data or simply visualize the data [11].

2.3Texture Analysis

texture analysis are usually categorized into four Approaches: first is **Structural** approaches represent texture by well-defined primitives (*microtexture*) and a hierarchy of spatial arrangements (*macrotexture*) of those primitives. To describe the texture, one must define the primitives and the placement rules. The choice of a primitive (from a set of primitives) and the probability of the chosen primitive to be placed at a particular location can be a function of location or the primitives near the location. The advantage of the structural approach is that it provides a good symbolic description of the image; however, this feature is more useful for synthesis than analysis tasks.

Second is **statistical** approaches represent the texture indirectly by the non-deterministic properties that govern the distributions and relationships between the grey levels of an image. Methods based on first (statistics given by individual pixel) and second-order statistics (statistics given by pairs of pixels) have been shown to achieve higher discrimination rates than the power spectrum (transform-based) and structural methods. The most popular second-order statistical features for texture analysis are derived from the so-called co-occurrence matrix. They were demonstrated to feature a potential for effective texture discrimination in biomedical-images.

Third is **Model based** texture analysis is using fractal and stochastic models, attempt to interpret an image texture by use of, respectively, generative image model and stochastic model. The parameters of the model are estimated and then used for image analysis. In practice, the computational complexity arising in the estimation of stochastic model parameters is the primary problem. The fractal model has been shown to be useful for modeling some natural textures

The last one is **Transform methods** of texture analysis, such as Fourier, Gabor and wavelet transforms represent an image in a space whose co-ordinate system has an interpretation that is closely related to the characteristics of a texture (such as frequency or size)[12].

2.4 Literature Review

In the last decade, many research activities were conducted to different methods to detect and classify the brain tumor (different type of tumor) in digital image, some papers are summarized below:

Shweta Jain, Shubha Mishra; they proposed a presents the artificial neural network approach namely Back propagation network (BPNs) and probabilistic neural network (PNN) to classify brain cancer. It is used to classify the type of tumor in MRI images of different patients with Astrocytoma type of brain tumor. The image processing techniques are used in this system is to isolate the tumor region from the rest of the image or separate the tumor region From the MRI images composed from (Histogram Equalization, Segmentation by Threshold method). Gray Level Co-occurrence Matrix (GLCM) is used to achieve the feature extraction. Then used Back propagation method which is a supervised learning method. Probabilistic neural networks (PNN) are a kind of radial basis network suitable for classification. The whole system worked in two modes firstly Training/Learning mode and secondly Testing/Recognition mode [2].

V.P.Gladis Pushpa Rathi and Dr.S.Palani proposed a novel method to classification brain tumor using Linear Discriminant Analysis which includes this steps, Image collection, Normalization, Intensity, shape and Texture feature extraction, feature selection and classification. In this method the shape, Intensity and Texture features are extracted and used for classification. Vital features are selected using Linear Discriminant Analysis (LDA). The results are compared with Principal Component Analysis (PCA) dimension reduction techniques. The number of features selected or features extracted by PCA and the classification accuracy by The Support Vector Machine (SVM) is 98.87%. then train the system by both continuous and without continuous data to minimize the error rate as well as increase the classification accuracy[13].

R. J.Deshmukh and R.S Khule; they proposed Neuro-fuzzy systems use the combined power of two methods: fuzzy logic and artificial neural network (ANN) using to detect the brain tumor. The work carried out involves processing of MRI images of brain cancer affected patients for detection and Classification on different types of brain tumors. A suitable Nero Fuzzy classifier is developed to recognize the different types of brain tumors. Steps which are carried out for detection of tumor are enlisted below:

Step1: Consider MRI scan image of brain of patients.
Step2: Train the neural network with database images.

Step3: Test MRI scan with the knowledge base.
Step4:Two cases will come forward (Tumor detected and Tumor not detected).
The features extracted from image are further given to Neurofuzzy classifier which is used to detect candidate circumscribed tumor. Generally, the input layer consists of seven neurons corresponding to the seven features. The output layer consists of one neuron indicating whether the MRI is a candidate circumscribed tumor or not, and the hidden layer changes according to the number of fuzzy rules that give best recognition rate for each group of features. [14].

P.B.Nikam and V.D.Shinde proposed brain image classification and detection using distance classifier method, this theses presents a system for automatic classification of healthy or affected person using Region growing segmentation by watershed algorithm, Euclidean distance classifier for fast computation, accompanied with preprocessing and post processing method apply on database consisting both normal and timorous samples of MR brain images. This system had two main stages, first is pre-processing of MRI images and then other post processing operations, which includes operations like noise removal, convert input image into gray scale image, High pass filter. Segmentation process using Threshold segmentation; it is the most common approach for detecting meaningful discontinuities in gray level, second applied Morphological operations and feature extracting process. Their work used Watershed for segmentation and considers the gradient magnitude of an image as a topographic surface and Euclidean distance classifier; this classifier based on the distance measure is direct and simple. The mean class values are used as class centers to calculate pixel-center distances for use by the Euclidean distance rule. For majorlevel classification of a homogeneous area this scheme is better. Its advantageous nature comes from the minimum time it takes to classify Distance Measures are used to group or cluster brightness values together.The results ensures that the method is efficient, and satisfying for quick detection whether person is healthy or unhealthy [15].

CHAPTER THREE

THEORETICAL FUNDAMENTAL

CHAPTER THREE
3.THEORETICAL FUNDAMENTAL

Medical images can obtain by different modalities but all imaging modalities can be divided into those that show body anatomy and those that show metabolic activity or function. One of the Anatomical Imaging is Magnetic Resonance Image (MRI) one of its objectives used to detect the brain tumors.

3.1 Brain Tumor

Brain has a very complex structure and is considered as a kernel part from the body and it is a soft, spongy mass of tissue. It is protected by: The bones of the skull, Three thin layers of tissue (meninges) and Watery fluid (cerebrospinal fluid) that flows through spaces between the meninges and through spaces (ventricles) within the brain [16].

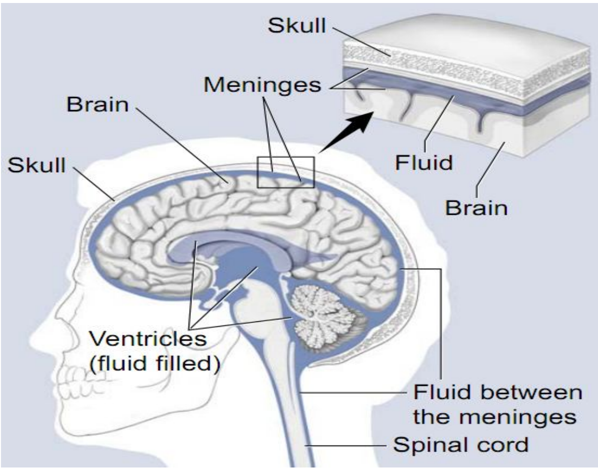

figure3. 1show the brain and nearby structure[16]

A brain tumor or intracranial neoplasm occurs when abnormal cells form within the brain[17]. Intracranial tumours are a diverse group of tumours that differ in localization, symptoms, histological composition and the occurrence of some species depend on age. The most common symptoms are limb movement disorder, numbness, vision, speech or mental changes. Another group of symptoms are resulted from local brain tissue irritation manifested as different types of seizures. Syndrome of increased intracranial pressure is referred to a set of symptoms, which include mainly headache, vomiting and visual disturbances[18].

3.1.1 Type of Brain Tumors:

There are more than 100 types of brain and spinal cord tumors (also called central nervous system or CNS tumors). They are usually named after the cell type they started in [19]but there are two basic kinds of brain tumors; primary brain tumors and metastatic brain tumors

3.1.1.1Primary Brain Tumors:

Primary brain tumors start, and tend to stay, in the brain; there are several type of primary tumor described below:

A. Malignant Tumor

Malignant tumours usually grow rapidly and spread within the brain and spinal cord. Malignant brain tumours can also be life-threatening. About 40% of brain and spinal cord tumours are malignant [19]. These include:

High-grade astrocytomas: Astrocytomas are tumors that are thought to arise from astrocytes—cells that make up the “glue-like” or supportive tissue of the brain, Grade II to IV tumors have increasing degrees of malignancy. Grade II astrocytomas have slightly unusual looking cells. The cells of a grade III and IV astrocytoma are very abnormal in appearance.

Oligodendrogliomas: These tumors arise from oligodendrocytes, one of the types of cells that make up the supportive, or glial, tissue of the brain. Oligodendrogliomas can be low-grade (grade II) or high-grade (grade III also called anaplastic).

Ependymomas: These tumors are usually located along, within, or adjacent to the ventricular system, often in the posterior fossa or in the spinal cord. Based on the appearance of the cell patterns when viewed under a microscope, this group of tumors can be sub-divided into smaller groups based on the appearance of their cell patterns.

*Glioblastoma:*Also called “astrocytoma, grade IV” and “GBM”“Grade IV astrocytoma,” “glioblastoma,” and “GBM” are all names for the same tumor. This tumor represents about 17% of all primary brain tumors and about 60-75% of all astrocytomas. They increase in frequency with age, and affect more men than women. Only three percent of childhood brain tumors are glioblastomas.Glioblastoma is generally found in the cerebral hemispheres of the brain, but can be found anywhere in the brain or spinal cord.

*Mixed gliomas:*mixedgliomas commonly contain a high proportion of more than one type of cell. Most often these tumors contain both astrocytes and oligodendrocytes(oligoastrocytoma).

In some malignant tumours, the cells are confined to one area. In other tumours, malignant cells are also found in surrounding tissue [20].

B. Benign Tumor

Benign tumors are typically surrounded by an outer surface (fibrous sheath of connective tissue) or remain with the epithelium [21].Benign tumours usually have slow-growing cells and clear borders (margins), and they rarely spread. However, they may be found in essential areas of the brain that control vital life functions, which can make them life-threatening .Some benign brain tumours can develop into a rapidly growing malignant tumour [19]. This process is called malignant transformation.The most common types are:

Meningiomas: These tumors arise from the “arachnoid mater” —one of the layers of the meninges (the lining of the brain). Meningiomas represent about 34% of all primary brain tumors and occur most frequently in middleaged women. The majority of meningiomas are benign, grade I, slow-growing tumors which are localized and non-infiltrating. Meningiomas are most often located between the cerebral hemispheres (“parasaggitalmeningiomas”) or over (“convexity meningiomas”) at the base of the skull, and in the back, lower part of the brain called the posterior fossa.

Acoustic Neuroma: Also called Neurilemmoma, Vestibular Schwannoma or Neurinoma .The acoustic neuroma is a benign tumor of the nerve of hearing (the 8th cranial nerve). It is located in the angle between the cerebellum and the pons, in the posterior fossa (the back of the skull).

A chondroma : This rare, benign tumor tends to arise at the base of the skull, especially in the area near the pituitary gland. it is generally might be present for a long time before causing any symptoms. A chondroma can grow to a large size, and may occur as a single or as multiple tumors.

*Craniopharyngioma (Grade I):*Acraniopharyngioma is a rare tumor that usually forms just above the pituitary gland. it can form from different types of brain or spinal cord cells[17].

*cysticastrocytomas:*ItisGrade I tumors include pilocyticastrocytomas, which are usually localized tumors and are often cured with surgical removal[20].

3.1.1.2 Metastatic Brain Tumors:

Cancer cells that begin growing elsewhere in the body and then travel to the brain form metastatic brain tumors. For example, cancers of the lung, breast, colon and skin (melanoma) frequently spread to the brain via the bloodstream or a magnetic-like attraction to other organs of the body. All metastatic brain tumors are, by definition, malignant, and can truly be called “brain cancer ” [20].

3.1.2 Tumor Grade:

The grade of a tumor refers to the way the cells look under a microscope [16]:

- Grade I: The tissue is benign. The cells look nearly like normal brain cells, and they grow slowly.

• Grade II: The tissue is malignant. The cells look less like normal cells than do the cells in a Grade I tumor.

• Grade III: The malignant tissue has cells that look very different from normal cells. The abnormal cells are actively growing (anaplastic).

• Grade IV: The malignant tissue has cells that look most abnormal and tend to grow quickly.

3.2 Magnetic Resonance Image (MRI)

Magnetic resonance imaging (MRI) is a type of scan that uses strong magnetic fields and radio waves to produce detailed images of the inside of the body, The results of an MRI scan can be used to help diagnose conditions, plan treatmentsand assess how effective previous treatment has been[22].

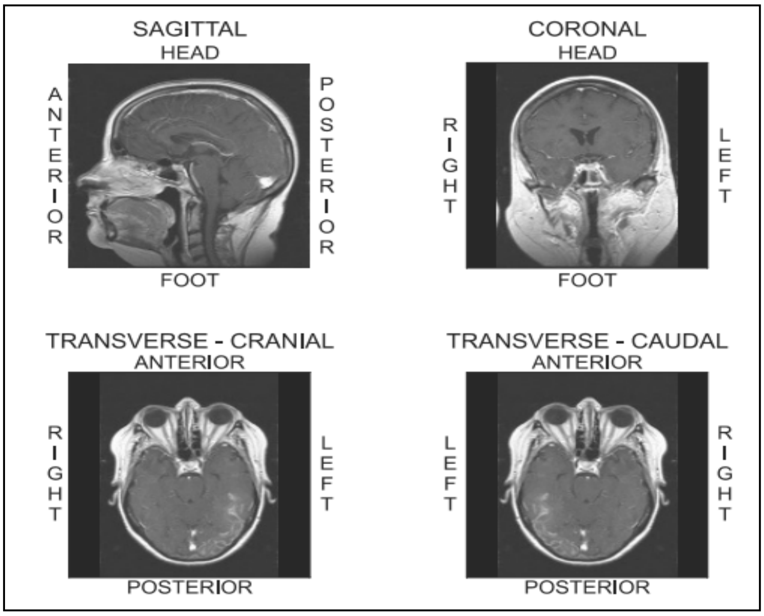

figure3. 2show standard slice directions in MRI[23]

3.2.1 Optimal Processing of Brain MRI [24]:

The ultimate goal of medical image analysis in general and brain magnetic resonance imaging (MRI) analysis in particular, is to extract important clinical information that would improve diagnosis and treatment of disease. In the past few years, MRI has drawn considerable attention for its possible role in tissue characterization. The image gray levels in MRI depend on several tissue parameters, including proton density (PD); spin-lattice (T1) and spin-spin (T2) relaxation times; flow velocity (*v*); and chemical shift . A sequence of MRI images of the same anatomical site (an MRI scene sequence) contains information pertaining to the tissue parameters. This implicit information is used for image analysis. In brain tumor studies, existence of abnormal tissues is easily detectable most of the time. However, accurate and reproducible segmentation and characterization of abnormalities are not straightforward. For instance, a major problem in tumor treatment planning and evaluation is determination of the tumor extent[24]. In an image analysis system designed for brain studies summarized in several steps These image analysis steps are shown in fig(3.3).

3.2.1.1Preprocessing

the consists of Preprocessing of brain in MRI these tasks are explained in the following sections.

A. **Registration**

To follow sequential changes that may occur over time, it is necessary to register the image sets obtained at different times. Also, if the patient moves between different scans, images should be registered before multispectral image processing and analysis are applied fig(3.4) .Several methods have been proposed for medical image registration . These techniques can be partitioned into three categories: (a)landmark based (point matching); (b) surface based (surface matching); and (c) intensity based (volume matching).

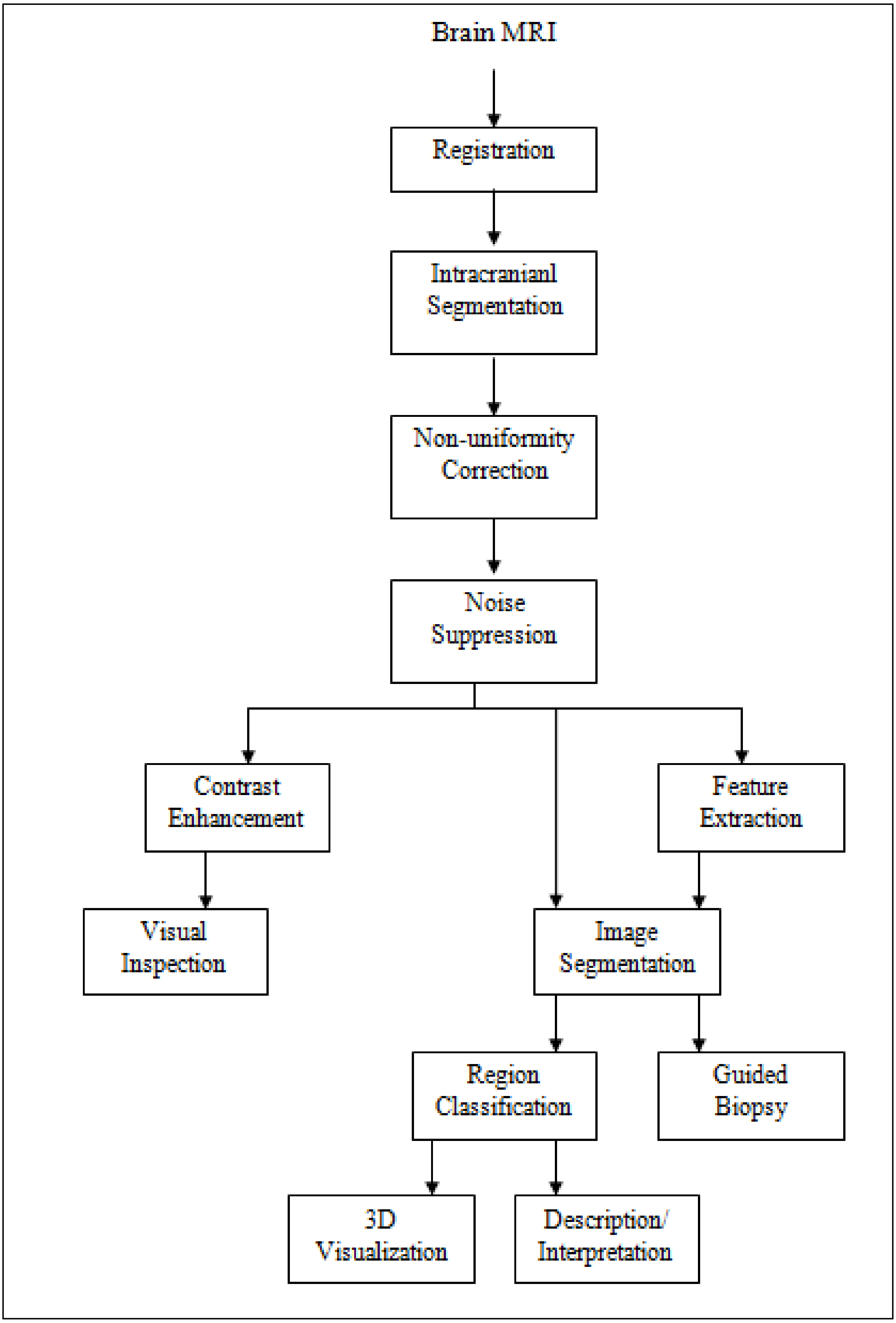

figure3. 3 A flowchart of image-processing steps for analysis of brain MRI studies[24]

B. **Intracranial Segmentation:**

The image background does not usually contain any useful information but complicates the image restoration and tissue segmentation/classification and increases the processing time. It is therefore beneficial to remove the image background before image restoration and analysis begins. In addition, in brain studies, tissues such as scalp, eyes, and others that are outside of the intracranial cavity are not of interest. Hence, it is preferred to segment the intracranial cavity volume from scalp and background. This segmentation is usually straightforward for brain MRI studies. Thresholding and morphological operators have been used to do this segmentation.

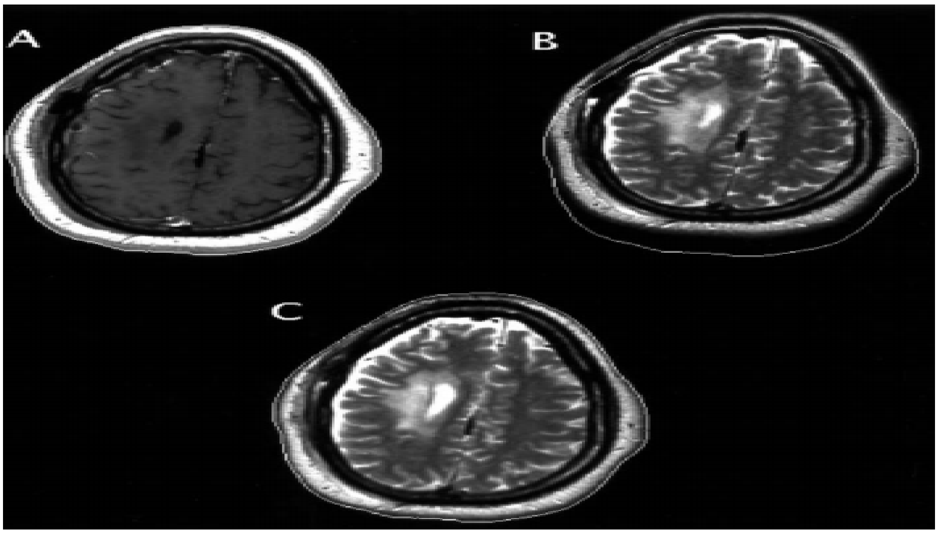

figure3. 4 An illustration of image registration.

A, An axial T1-weighted MRI of a tumor patient, with skin edges (contour) overlaid. B, Corresponding axial T2-weighted MRI, with contour of the T1-weighted image overlaid to show the need for registration. C, The T2-weighted image after being registered to the T1-weighted image, with the contour of theT1-weighted image overlaid to illustrate the match generated by the image registration method[24]

C. **Nonuniformity Correction:**

MRI brain images acquired using standard head coils suffer from several possible sources of nonuniformity, including (a) main field (B_0) nonuniformity;

(b) the time domain filter applied before Fourier transformation in the frequency encoding direction; (c) nonuniformity caused by uncompensated gradient eddy currents; (d) transmitted and received radiofrequency (RF) field nonuniformity; (e) RF penetration depth effects; and (f) RF standing wave effects. The first effect is usually corrected by using a multiple spin-echo sequence. However, because most of the current scanners use digital filters whose effect on the image is limited to two or three pixels at the edge of the image, this correction is usually unnecessary. The third effect on modern MRI systems, such as GE signa, that are equipped with shielded gradients is small for spin-echo sequences at long repetition times used in tumor studies. The fourth effect needs to be estimated and used to correct MRI scans. The fifth and sixth effects are normally negligible in tumor patient studies; thus, no correction is necessary for them.

D. Tissue In Homogeneities:

A tissue type may have biological variations throughout the imaged volume. For example, biological properties of white matter in the anterior and posterior of the brain are slightly different. A tissue type may also have biological heterogeneity in it; many brain lesions are heterogeneous in nature. These cause variations of signal intensity for a single tissue in the imaged volume. The feature space representation of the entire volume may therefore be spread out (i.e., clusters for different tissues may overlap). Sources of this variation include the difference in the proton density and T1 and T2 relaxation times from voxel to voxel. These differences generate a different multiplicative factor in image gray levels from voxel to voxel, and application of a ratio filter seems appropriate. However, in general, because of these effects, feature space analysis is not recommended for the entire 3-D volumein one stage; superior results may be obtained using a slice-by-slice analysis approach.

E. Noise Suppression

Noise limits the performance of both human observers and computer vision systems. As such, noise should be suppressed before inputting data to image segmentation and classification algorithms. To reduce the computation time, noise suppression is performed after intracranial volume segmentation. General purpose filters such as low-pass, Weiner, median, or anisotropic diffusion filters may be used.

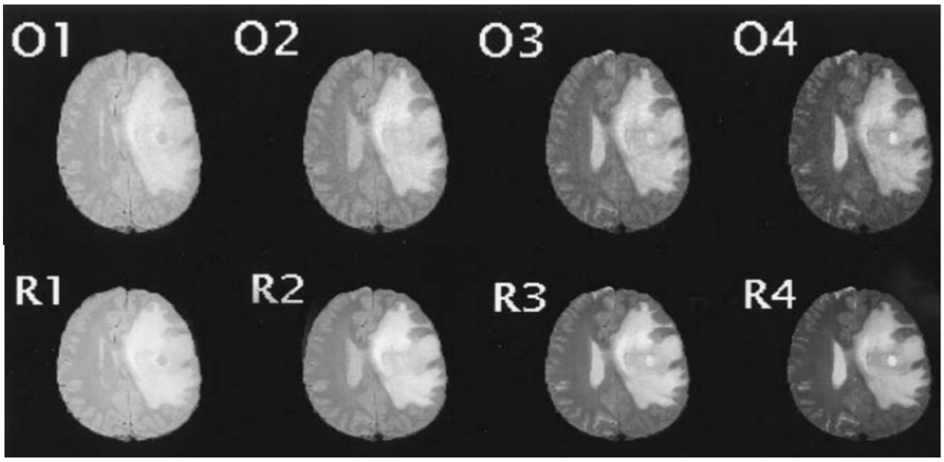

figure3. 5 Noise-suppression and filter .O1–O4, Four T2-weighted multiple spin echo images and a T1-weighted image of a tumor patient, respectively, after registration and intracranial segmentation. R1–R4, Noise-suppressed images generated using the filter[24]

3.2.1.2 Contrast Enhancement

Contrast/noise ratio is one of the standard measures of MR image quality. There are at least three approaches for improving the image CNR: (a) by injecting contrast agents to the patient; (b) by optimizing MRI protocols and pulse sequence parameters; and (c) by combining multiple MR images obtained Inclinical studies.

3.2.1.3Feature Extraction

Brain tumors are normally large, and detection of their presence is simple. They may be found by a symmetry analysis of the image gray levels in the axial images, because they generate significant gray level asymmetry in these images. Detection of multiple zones in the tumor and accurate estimation of the tumor extent are, however, difficult, and different image analysis approaches may be used for this purpose.

3.2.1.4Image Segmentation:

Tumor segmentation methods are mainly region based. They use MRI pixel intensities or features extracted from them as representatives of biological properties of tissue. Image pixels are classified into different regions on the basis of these features. Classification is done using a decision method such as those explained in the next section.

3.3Artificial Neural Networks:

Artificial neural networks is one of applications of artificial intelligent and it has a wide used in medical diagnosis system.

3.3.1 Architecture of ANNs:

An artificial neural network (ANN) is a computational model that attempts to account for the parallel nature of the human brain. An (ANN) is a network of highly interconnecting processing elements (neurons) operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. A subgroup of processing element is called a layer in the network. The first layer is the input layer and the last layer is the output layer. Between the input and output layer, there may be additional layer(s) of units, called hidden layer(s) [25]show in figure(3.6) .the mathematic operation for each perceptron or processing element(neuron) describe in figure(3.7).The weights in an ANN express the relative strengths (or mathematical values) of the various connections that transfer data from layer to layer. In other words, the weights express the relative importance of each input to a Processing element.

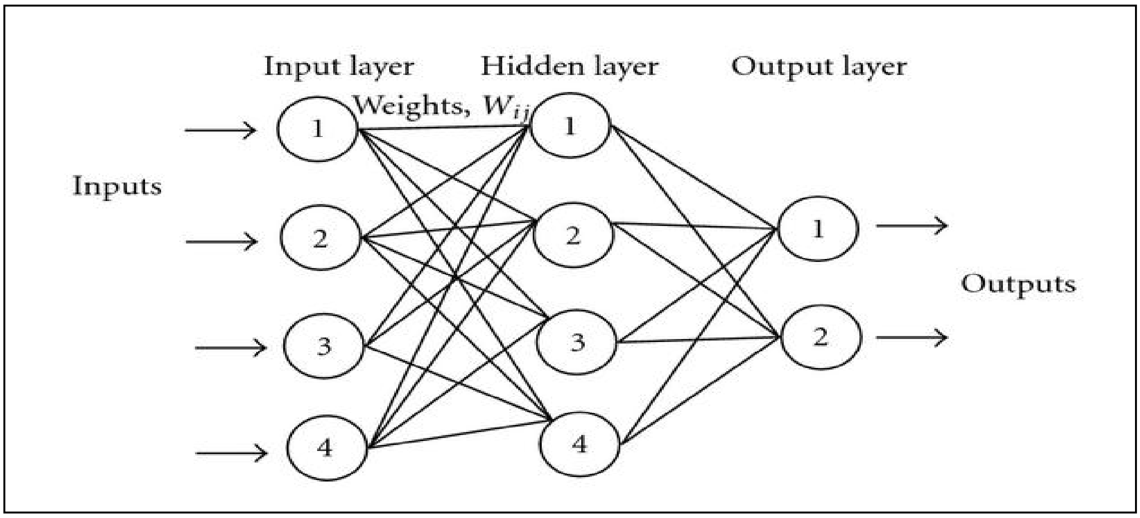

figure3. 6 Three-layered feed-forward artificial neural network configuration.

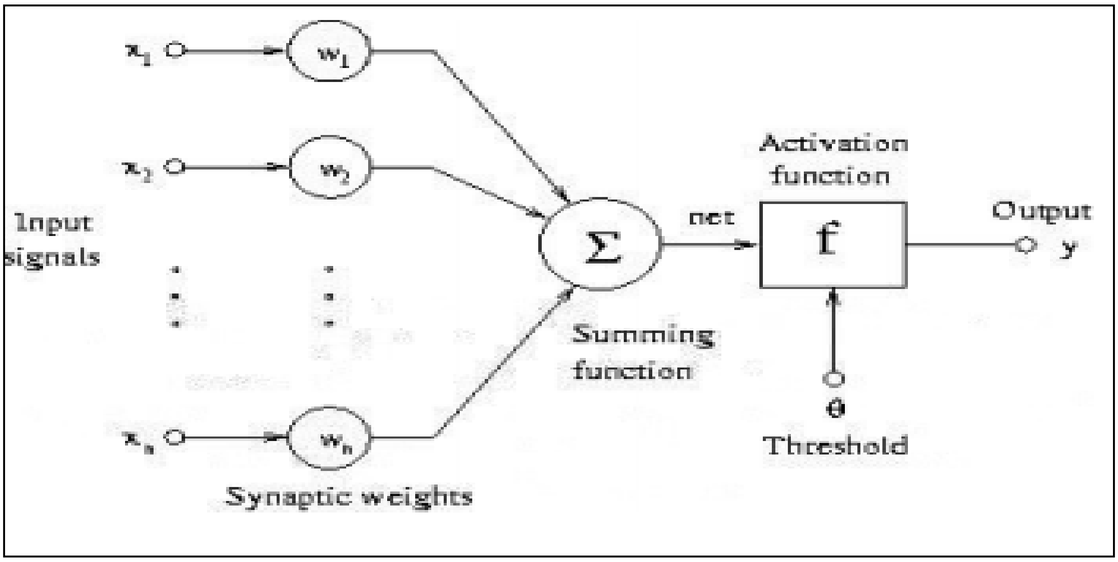

figure3. 7 mathematical model of discrete perceptron or neuron[26]

From figure (3.7) Where: x is input, w is weight and y is output ,the activation of perceptron by flowing equation(1)&(2) and learning rule by Eq.3.

$$y = f\left(\sum_{j=1}^{n1`} w_j x_j - \theta\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$y = f\left(\sum_{j=1}^{n} w_j x_j\right), \quad x_{n+1} = -1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

f = threshold function: unipolar [27] or bipolar {-1,+1}

$$x_{k+1} = x_k - \alpha_k g_k \text{..(3)}$$

Where: x_k is a vector of current weights and biases, g_k is the current gradient and α_k is learning rate.

3.3.2 Artificial Neural Networks Learning:

After designed the ANNs it must be learned on information understanding, learn simply mean adjusting ANN weight until the network understand the input information. There are two ways for artificial neural network learning which are supervised learning and unsupervised learning.

A. Supervised Learning

In the supervised learning approach, we use a set of inputs for which the appropriate outputs are known In one type, the difference between the desired and actual outputs is used to calculate corrections to the weights of the neural network (learning with a teacher) .this process, known as the back propagation of error is repeated until the evolved sets of weights best reproduces the entire training and testing database results in an answer that is most accurate. After the learning phase, the network is given the input data and it gives its best answer based on prior learning[28].

B. Un Supervised Learning

In unsupervised learning, the desired response is not known a priority. Thus, explicit error information in unavailable to improve network behavior. Since no information is available as to the correctness or incorrectness of the response, learning must somehow be accomplished based on observation of responses to inputs that yield marginal or no knowledge about them. The network is therefore training towards some optimum output where optimum is usually some clustering of the data[28].

In almost all applications of artificial neural networks in the field of cancer research, the target or desired output is explicitly provided. Almost invariably medical experts assist with the most likely diagnosis given a certain set of pathological information. Similarly, prognostic information is based on survival analysis procedures, and patient management is optimized through retrospective assessment of previous and long-term responses to treatment. Thus, in the vast majority of neural structures described in this book, supervised learning constitutes the basic mode of learning.

CHAPTER FOUR

METHODOLOGY

CHAPTER FOUR
4.METHODOLOGY

4.1 Overview of Methodology

This chapter describes and discuss the research methods that were used for this study brain tumor detection. It can be summaries in three stages .In first stage it start with pre-processing of MRI images to enhancement it and make it more suitable to analyze such as reduce and remove noise, contrast enhancement, and image sharpening[29]. Second stage is processing of images like edge detection, segmentation, morphological operations feature selection and extraction, classification etc. Final stage is implement the feature of images for pattern recognition to detect the tumor. The propose method described in flowchart fig.4.1.

4.2 Database

In this thesis used digital magnetic resonance image database which were obtained from Whole Brain Atlas website that collected from the Harvard University, medical educational school and various sources[30]. The MRI brainimages are taken of person above 20 years age group as there are no significant changes observed in image pattern after 18 years of age. Database consists of images of both male and female. In this database, every image is 256× 256 pixels and 8-bit gray level scale. It consists of 239 images which belong to normal and abnormal(with and without tumor) brain image. This data downloaded in*gif* format but were changed to *png* format before used it through Matlab environment.

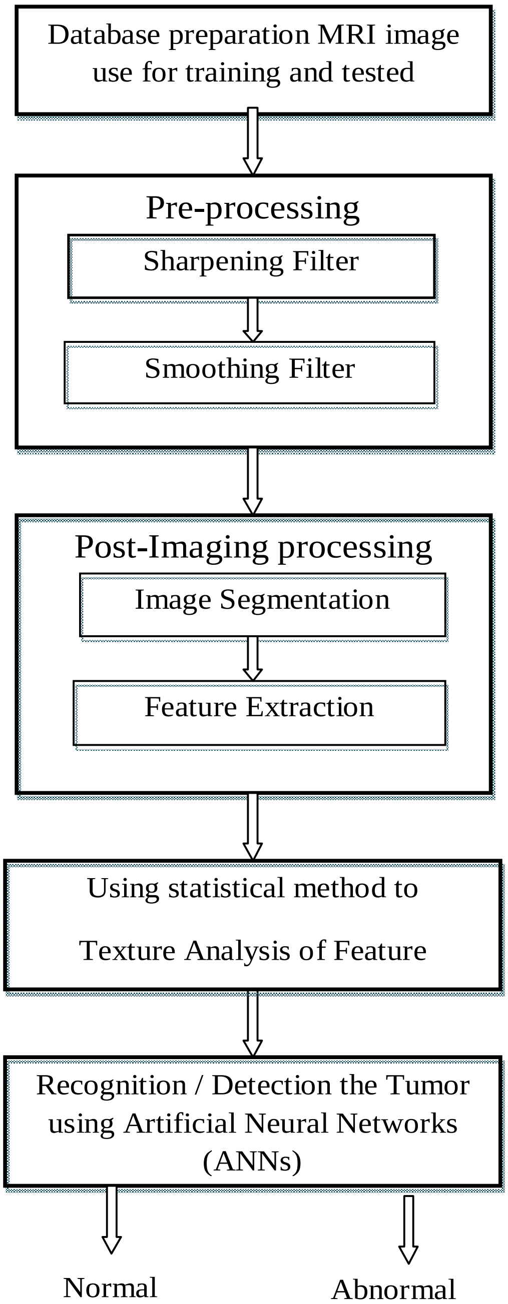

figure4. 1flowchart of proposal system.

4.3 Preprocessing Stage

The pre-processing stage that applied in this study is used to enhancement the images and make it more suitable for analysis. Some process like reduce and remove noise, and image sharpening are obtained in the flowing paragraphs.

4.3.1 Sharpening Filter

In this research used Laplacian filter which one of Spatial Sharpening Filters. Also Laplacian filter is a second-order derivative. It is better to enhance fine detail (including noise) much more than a first-order derivative[29].The principal objective of sharpening is to highlight fine detail in an image or to enhance detail that has been blurred, either in error or as a natural effect of a particular method of image acquisition. The digital implementation of the two-dimensional Laplacian in Eq. (4) is obtained by summing these two components:

$$\nabla^2 f(x,y) = [f(x+1,y) + f(x-1,y) + f(x,y+1) + f(x,y-1)] - 4f(x,y) \qquad \ldots\ldots\ldots\ldots(4)$$

4.3.2 Smoothing Filter

The laplacian filter sharped all final details of imaging including the noise; that requires smoothing filter to remove or reduce this noise. So in this research used Averaging filter which one of Spatial Smoothing Filters. The response of a smoothing, linear spatial filter is simply the average of the pixels contained in the neighborhood of the filter mask. In general, average filtering of an image *f(x,y)* of the size $M\times N$ with a weighted averaging filter of size $m\times n$ (*m* and *n*odd) is given by the expression (5)

$$g(x,y) = \frac{\sum_{s=-a}^{a}\sum_{t=-b}^{b} w(s,t)\, f(x+s,y+t)}{\sum_{s=-a}^{a}\sum_{s=-b}^{b} w(s,t)} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

where, $a=(m-1)/2$ and $b=(n-1)/2$. To generate a complete filtered image *g(x,y)* this equation must be applied for $x=0, 1,2,\ldots, M-1$ and $y=0, 1, 2,\ldots, N-1$. After applied the preprocessing filters calculated the error by measure Mean square error (MSE) between the original MRI image and preprocessing image to measure the degradation that happen in original image or loss it is information.

$$NMSE = \frac{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}[f(m,n)-g(m,n)]^2}{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}[f(m,n)]^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

Where: *f(m,n)* is original image, *g(m,n)* preprocessing image and *M,N* images size.

4.4 Post- Processing Stage

The post-processing stage that applied in this study is used to extract the region of tumor from images. Some process like image segmentation, morphological operation and feature extraction are obtained in the flowing paragraphs:

4.4.1 Image Segmentation

Brain Magnetic Resonance Imaging (MRI) segmentation is a complex problem in the field of medical imaging despite various presented methods. In this work used threshold method. Thresholding has been used for segmentation as it is most appropriate for the present system in order to achieve a binarized image with gray level (1) representing the tumor and gray level (0) representing the background [27]. The value of threshold calculated by mean gray level(T) in Eq.(7) .The main purpose of the segmentation in this project to segment the MRI image just to tumor and background.

$$T = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} f(x,y)}{M \times N} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

Where $f(x,y)$ is gray level of the pixel in coordinated (x,y) of MRI image and MxN is the size of MRI image.

$$f_s(x,y) = \begin{cases} 255, & f(x,y) \geq T \\ 0, & f(x,y) < T \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

Where $f_s(x,y)$is thresholding image or binarization image.

4.4.2 Morphological Operations

After segmentation the image to binary image, the binarized image needs some operations to enhance the region of tumor, because the segmentation of brain tumors in magnetic resonance images (MRI) is the very difficult because the variety of their possible shapes, locations and image intensities[31].however in this work the morphological operations is applied. The main process of the morphological operators is opening, closing, erosion, and dilation that remove the hurdle and small holes from the image. The morphological operations used in this research are erosion and dilation these operations are fundamental of morphological processing[29]. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the *structuring element* used to process the image, applied by matlab functions *imerode* and *imdilate* for erosion and dilation respectively show by this expressions:

$$f_e(x,y) = imerode(f(x,y),E) \qquad (9)$$

$$f_e(x,y) = imdilate(f(x,y),E) \qquad (10)$$

Where: $f(x,y)$, binary image, $f_e(x,y)$, returning the eroded or dilated image. The argument E is a structuring element.

4.4.3 Feature Extraction

Feature extraction is the techniques or method that used to measure of difference characteristics of image segments also its process to represent raw image in its reduced form to facilitate decision making such as pattern classification. Each segmented region in a scene may be described by a set of such features In this work used texture analysis method; The Spatial Gray Level Dependency matrix(SGLD) matrix generator, which decomposes the input image into texture features(Haralick’s features)[32].

4.5 The Spatial Gray Level Dependency matrix(SGLD)

The SGLD matrix also known as the gray-level co-occurrence matrix (GLCM)is a statistical approach of examining texture that has been proven to be a very powerful tool for texture image segmentation and considers the special relationship between pixels of different gray levels.The SGLD is one of second-order statistics method of a texture image.

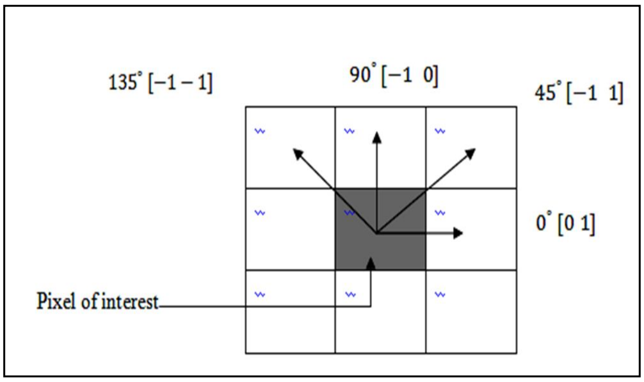

figure4. 2Direction for generation of SGLD matrix.

The SGLD matrix calculated between two pixels one of a certain intensity i occurs in relation with another pixel j. The SGLD matrix is describe by the relative frequencies$p(i,j,d,\emptyset)\{R.Haralick, 1973.\#26\}$.Un normalized frequencies of SGLD matrix for the distance d and orientation ∅ defined by this equations:

$$p(i,j,d,0^{\circ}) = \#\{((k,l),(m,n)) \in (L_x \times L_y) \times (L_x \times L_y) | k-m=0, |l-n| = d, I(k,l)=i, I(m,n)=j\} \quad (11)$$

$$p(i,j,d,45^{\circ}) = \#\{((k,l),(m,n)) \in (L_x \times L_y) \times (L_x \times L_y) | k-m=d, |l-n| = -d, or\ k-m=-d, |l-n| = d, I(k,l)=i, I(m,n)=j\} \quad (12)$$

$$p(i,j,d,90^{\circ}) = \#\{((k,l),(m,n)) \in (L_x \times L_y) \times (L_x \times L_y) | k-m=d, l-n=0, I(k,l)=i, I(m,n)=j\} \quad (13)$$

$$p(i,j,d,135^{\circ}) = \#\{((k,l),(m,n)) \in (L_x \times L_y) \times (L_x \times L_y) | k-m=d, |l-n| = d, or\ k-m=-d, |l-n| = -d, I(k,l)=i, I(m,n)=j\} \quad (14)$$

Where: # denotes the number of elements. It is observed that SGLD matrix is symmetrical because $p\ (i, j, d, \theta) = p\ (j, i, d, \theta)$.

In this work the SGLD matrix calculated from MRI images, firstly setting the size of the spatial gray level dependency matrix depend on the grey level of MRI image then used equations(11,12,13,14) , in angles of 0°, 45°, 90°, and 135° and d=1. Then used matrix to calculate texture feature of specific MRI image.

4.6 Texture Feature Extracted from SGLD matrix

Texture in one of the important characteristics used in identifying objects or regions of interest in an image[33], whoever in this project applied Haralick's feature from SGLD matrix.

4.6.1 Haralick's Features:

The Haralick's texture features are: Energy(EG), Correlation(CO), Inertia(IN), Entropy(EN), Inverse Difference Moment(IDM), Sum Average(SA), Sum Variance(SV), Sum Entropy(SE), Difference Average(DA), Difference Variance(DV), Difference Entropy(DE), Information measure of correlation-1(ICO-1) and Information measure of correlation-2(ICO-2).These features can be calculated by using the following equations:

Denote *P(i,j):(i,j)* then try in a normalized SGLD matrix N_g is Number of distinct gray levels in quantized image.

$$p_x(i) = \sum_{i=1}^{N_g} p(i,j) \ldots\ldots (15)$$

$$p_y(j) = \sum_{j=1}^{N_g} p(i,j) \ldots\ldots (16)$$

$$p_{x+y}(k) = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j) \ldots\ldots (17)$$

$$i + j = k, \qquad k = 2,3, \ldots .2N_g$$

$$p_{x-y}(k) = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j) \ldots\ldots (18)$$

$$|i - j| = k, \qquad k = 0,1, \ldots .N_g - 1$$

1. **Energy(EG):**

The Energy feature (EG) returns the sum of squared elements in the SGLD matrix as expressed by the following equation:

$$EG = \sum_i^{N_g} \sum_j^{N_g} \{p(i,j)\}^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (19)$$

2. **Entropy(EN):**

The Entropy coefficient (EN) is a descriptor of randomness produces a low value for an irregular SGLD matrix. It achieves its highest value when all elements of the SGLD matrix are equal for an irregular image. This coefficient is defined by the following expression:

$$EN = -\sum_i^{N_g} \sum_j^{N_g} p(i,j) \log\big(p(i,j)\big) \ldots\ldots\ldots\ldots\ldots\ldots(20)$$

3. **Inertia(IN):**

The Inertia (IN) also called Contrast feature is a measure of image intensity contrast or the local variations present in an image to show the texture fineness. This parameter is specified by the following equation:

$$IN = -\sum_i^{N_g} \sum_j^{N_g} (i-j)^2 p(i,j) \ldots\ldots\ldots\ldots\ldots\ldots\ldots..(21)$$

4. **Correlation(CO):**

The descriptor Correlation (CO) measures the linear dependence of gray level values in the co-occurrence matrix or describes the correlations between the rows and columns of the co-occurrence matrix. This parameter is specified by the following equation:

$$CO = \frac{\sum_i^{N_g} \sum_j^{N_g} (i-\mu_x)(j-\mu_y) p(i,j)}{\sigma_x \sigma_y} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (22)$$

Where μ_x,$\mu_{y,}\sigma_x and\ \sigma_y$ are the means and standers deviations of $p_x and\ p_y$.

5. **Inverse Difference Moment (IDM):**

Inverse Difference Moment is also called the "Homogeneity" Mathematically, it can be written as:

$$IDM = \sum_{i}^{N_g} \sum_{j}^{N_g} \frac{1}{1+(i-j)^2} p(i, j) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (23)$$

6. **Variance(VA):**

The Variance (VA) is a measure of variation. A variance of zero indicates that all the values are identical. A non-zero variance is always positive: A small variance indicates that the data points tend to be very close to the mean and hence to each other, while a high variance indicates that the data points are very spread out from the mean and from each other.

$$VA = \sum_{i}^{N_g} (i - \mu_x)^2 p_x(i) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (24)$$

7. Sum Average (SA)

$$SA = \sum_{k=0}^{2N_g-2} k p_{x+y}(k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (25)$$

8. Sum Entropy (SE):

$$SE = -\sum_{k=0}^{2N_g-2} p_{x+y}(k) \log_2 p_{x+y}(k) \ldots\ldots\ldots\ldots\ldots\ldots (26)$$

9. Sum Variance (SV)

$$SV = \sum_{k=0}^{2N_g-2} (k - SA)^2 p_{x+y}(k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (27)$$

10.Difference Entropy (DE)

$$DE = -\sum_{k=0}^{N_g-1} p_{x-y}(k) \log_2 p_{x-y}(k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (28)$$

11.Difference Average (DA)

$$DA = \sum_{k=0}^{N_g-1} k p_{x-y}(k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (29)$$

12.Difference Variance (DV)

$$DV = \sum_{k=0}^{N_g-1} (k - DA)^2 p_{x-y}(k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (30)$$

13. information measures of correlation 1:

$$inf1 = \frac{HXY - HXY1}{max\{HX, HY\}} \ldots\ldots(31)$$

14. information measures of correlation 2:

$$inf2 = (1 - exp[-2.0(HXY2 - HXY)])^{1/2} \ldots\ldots(32)$$

$$HXY = -\sum_{i}^{N_g}\sum_{j}^{N_g} p(i,j)\log(p(i,j)) \ldots\ldots (33)$$

$$HXY1 = -\sum_{i}^{N_g}\sum_{j}^{N_g} p(i,j)\log\{p_x(i)p_y(j)\} \ldots\ldots(34)$$

$$HXY2 = -\sum_{i}^{N_g}\sum_{j}^{N_g} p_x(i)p_y(j)\ \log\{p_x(i)p_y(j)\} \ldots\ldots (35)$$

After calculated all thirteen parameter by haralick equations, calculated correlation coefficient between them and plot the characteristics curve ; to choose the best parameter which have good performance and gives the true result to detect the tumor. That to facility the study parameters in the following terms:

- Homogeneous: the specific parameter must be homogeneity in one case (normal or abnormal in this project) and has a significant difference between the cases.
- Uncorrelated: also the parameters will choose as input to ANNs it must be uncorrelated between them every one it has different effect in image from another and Covering all properties of feature.
- Coherent: the parameter must be coherent and it does not has interface between them.

Finally, choose eight parameter that has best performance in neural networks training process : Energy, Inertia, Entropy, Inverse Difference Moment, Sum Variance, Sum Entropy, Difference Variance and Difference Entropy, This texture feature used as input parameters of image for back propagation neural networks to detect the tumor from MRI image (normal or abnormal) Appendix(A).

4.7 Artificial Neural Networks

In this project was used back propagation network which one of Artificial neural networks types.

4.7.1 Back propagation Network

Creating a Network: was Create feed-forward back propagation network by *newff* function in toolbox of matlab with three layers input layer with eight(8) preceptron or processing elements, hidden layer with twenty(20) preceptron or processing elements and output layer with two(2) processing elements. Also it requires three arguments and returns the network object. The first argument is a matrix of sample R-element input vectors. The second argument is a matrix of sample S-element target vectors. The sample inputs and outputs are used to set up network input and output dimensions and parameters. The third argument is an array containing the sizes of each hidden layer. (The output layer size is determined from the targets). It has 8-element input vectors that mean the best eight feature or parameter of images, 2-element target and output vectors for classifier the input to normal and abnormal(with or without tumor).

Training the Network: after create the network the training processing come. For this proposed used *train* function in toolbox of matlab. first identified the transfer function of the training to be used in each layer. was used tangent sigmoid transfer function fig4.3. Transfer functions calculate a layer's output from its net input by using training Algorithm[34]. The type of back propagation network training is supervised learning which it best method for simples that has nonlinear transformation like sigmoid transfer function. The weights in an ANN express the relative strengths(or mathematical values) of the various connections that transfer data from layer to layer. in supervised learning initializes the weights and biases of the network it can be automatically.

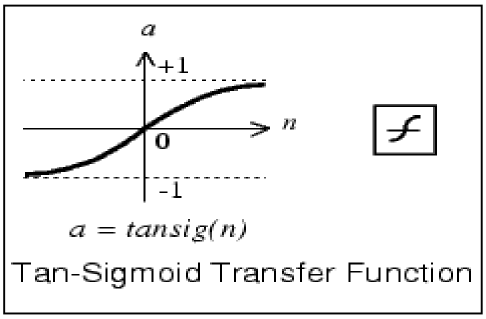

figure4. 3graph and simple of sigmoid transfer function

Back propagation Algorithm: There are many variations of the back propagation algorithm, the BPN for one iteration is obtained by Eq.36 to adjust the weights values.

$$x_{k+1} = x_k - \alpha_k g_k \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(36)$$

Where:$x_k$is a vector of current weights and biases, g_k is the current gradient and α_k is learning rate.

4.8 Graphic User Interface(GUI):

In this section was built window of Graphic User Interface(GUI) to describe all the proposed algorithm for brain tumor detection from load image to detect the tumor. The GUI window contains six panel:

- Panel of input data :is the start of proposed a logarithm which contains the MRI images that wanted to classify it.
- Panel of image processing: its composed from load original image, pre-processing, segmentation, morphological operation feature extraction and the tumor in original image.
- Panel of ANNs: recognition of artificial neural networks.
- Panel of axis: this contains eight axis to display the each step result of imaging processing.
- Panel of result of detection: display the result of detection; normal or abnormal.

- Panel consist from reset to restart the window of GUI and exit to close and exit from GUI window.

The algorithm described in this project is developed and successfully trained in Matlab version R2008 a using a combination of image processing and neural networktoolbox.

CHAPTER FIVE

RESULTS AND DISCUSSION

CHAPTER FIVE
5.RESULTS AND DISCUSSION

5.1 Results Overview

This section present and analysis the results of all a logarithm method that described in chapter three, The algorithm method successfully applied in Matlab version R2008 a using a combination of image processing and neural network toolbox.

5.1.1Results of Haralick's Features

This show all the statistical characteristics of haralick's features for normal and abnormal MRI images data processed from fig.5.1 to fig.5.13 to know the correct selection from the parameters and gives the true result of tumor detection, So it plotted in the curve and calculated the correlation between them to facility the study parameters in the following terms: Homogeneous , uncorrelated and coherent.

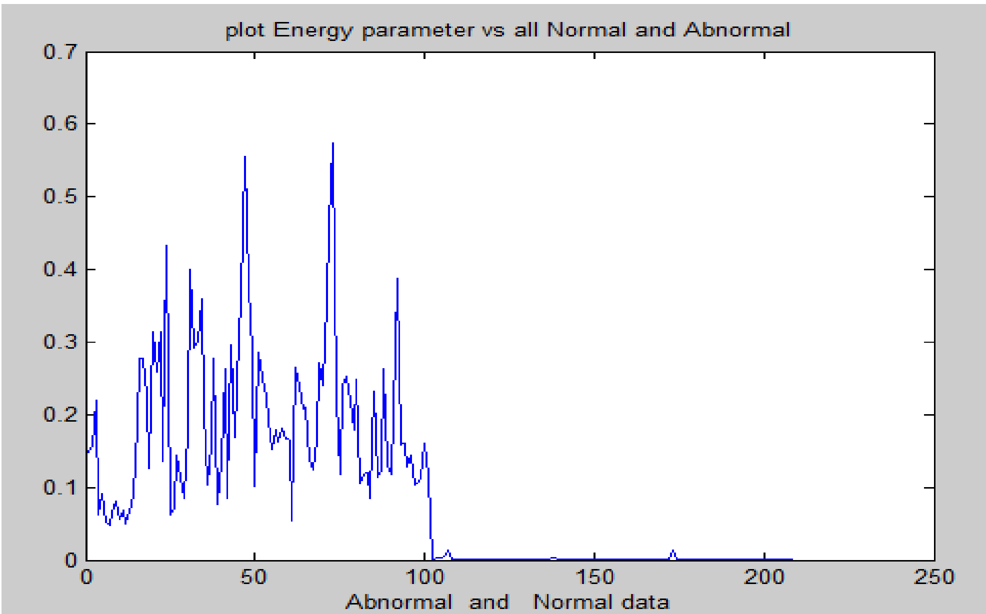

Figure 5. 1Energy's feature for 101 abnormal and 102 normal

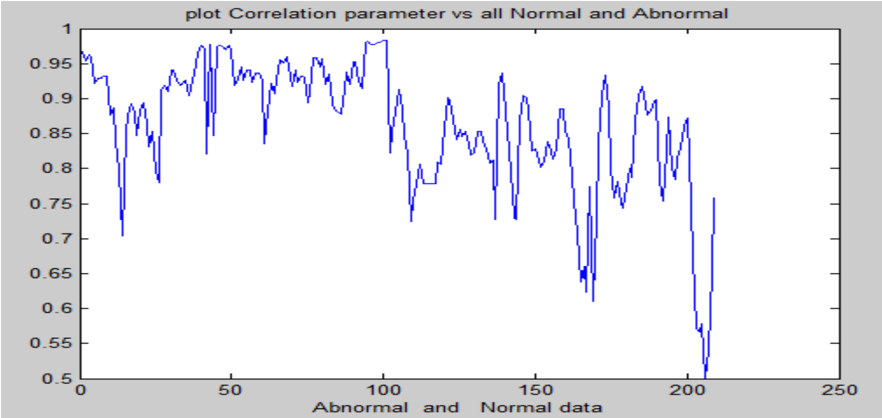

Figure 5. 2correlation’s feature for 101 abnormal and 102 normal.

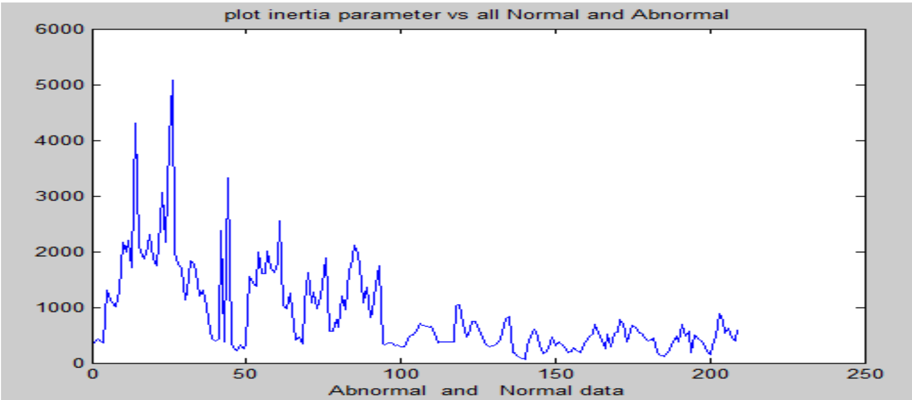

Figure 5. 3Inertia’s feature for 101 abnormal and 102 normal.

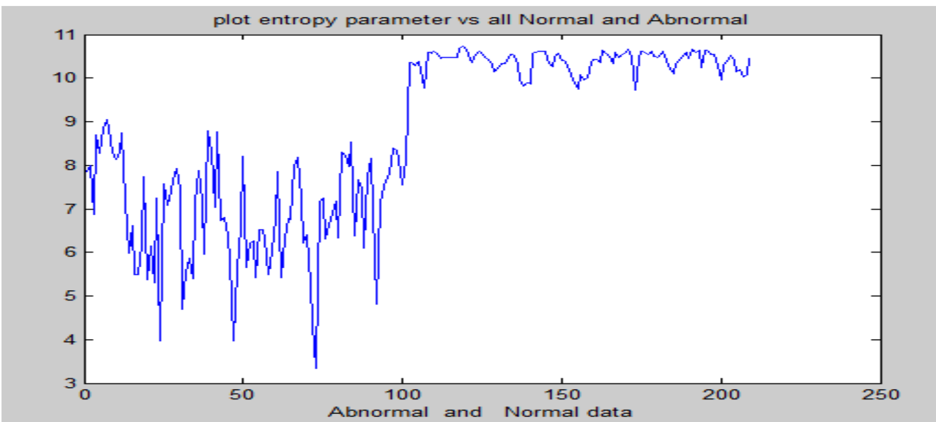

Figure 5. 4Entropy’s feature for 101 abnormal and 102 normal.

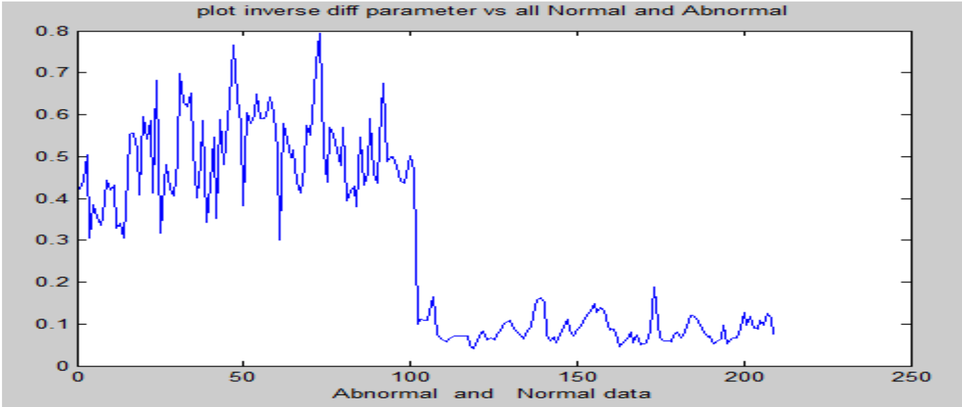

Figure 5. 5 Inverse Difference Moment's feature for 101 abnormal and 102 normal

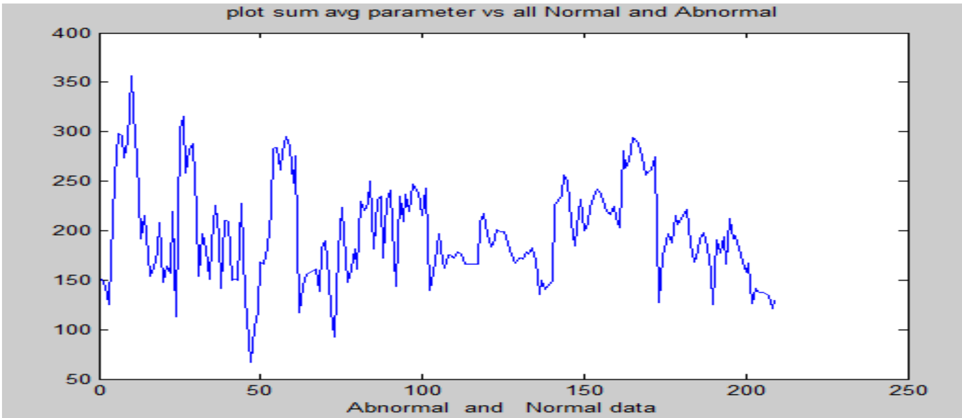

Figure 5. 6 Sum Average's feature for 101 abnormal and 102 normal

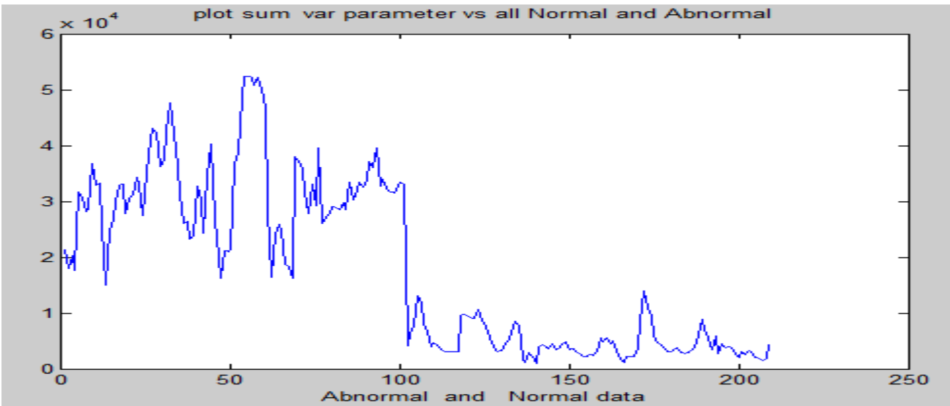

Figure 5. 7 Sum Variance's feature for 101 abnormal and 102 normal.

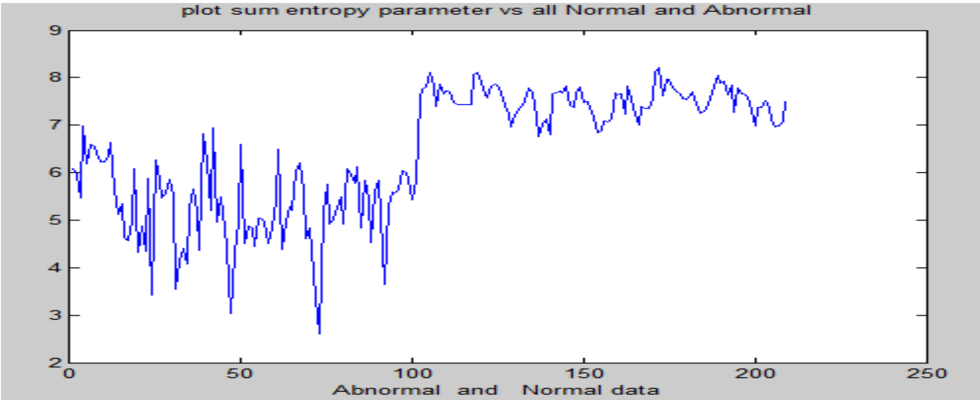

Figure 5. 8 Sum Entropy's feature for 101 abnormal and 102 normal.

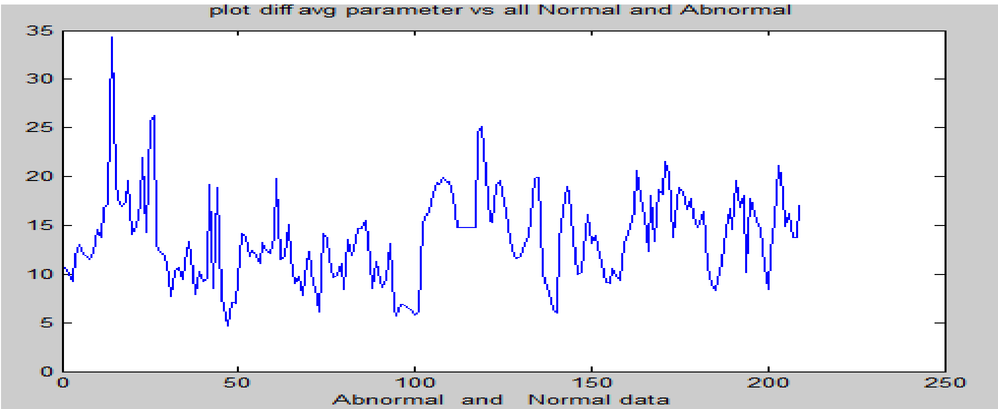

Figure 5. 9Diff-Average's feature for 101 abnormal and 102 normal.

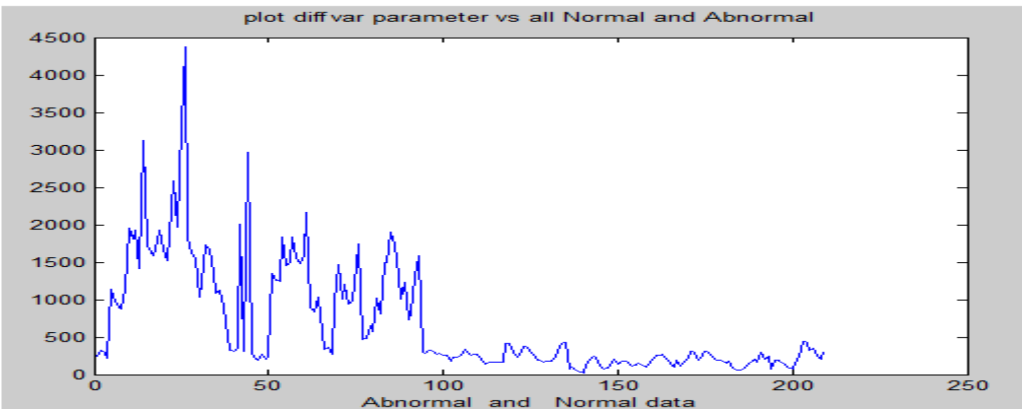

Figure 5. 10 Diff- Variance's feature for 101 abnormal and 102 normal.

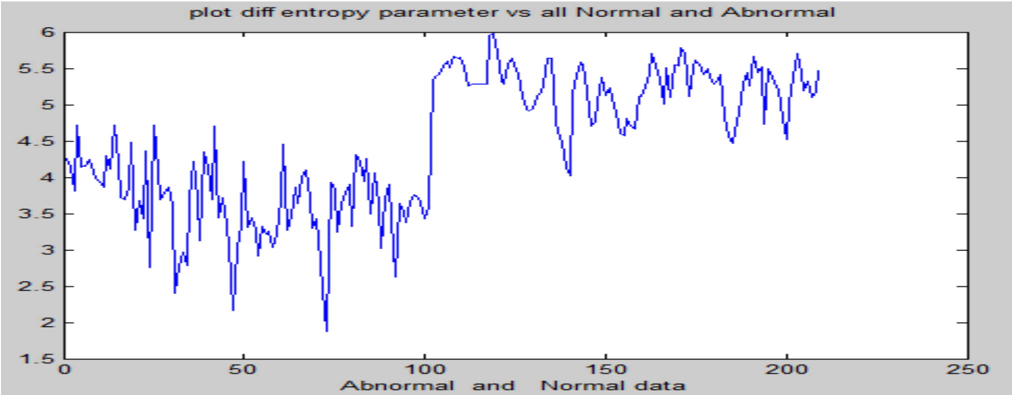

Figure 5. 11Diff- Entropy's feature for 101 abnormal and 102 normal.

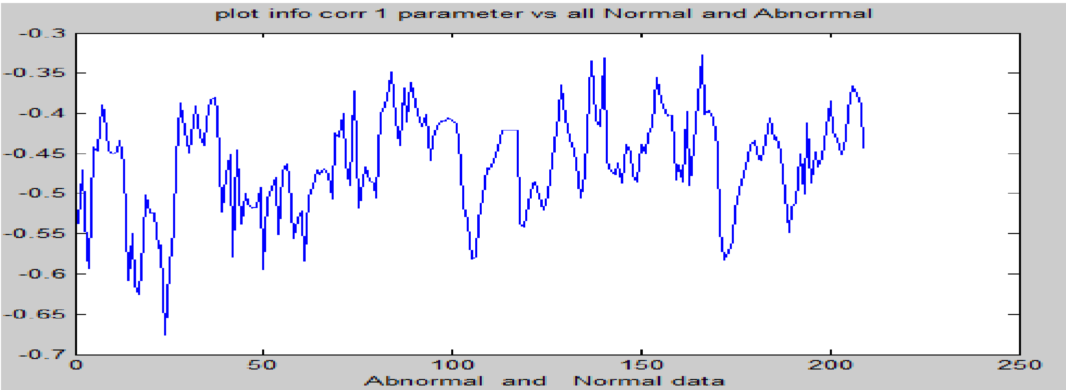

Figure 5. 12Info-correlation-1 feature for 101 abnormal and 102 normal

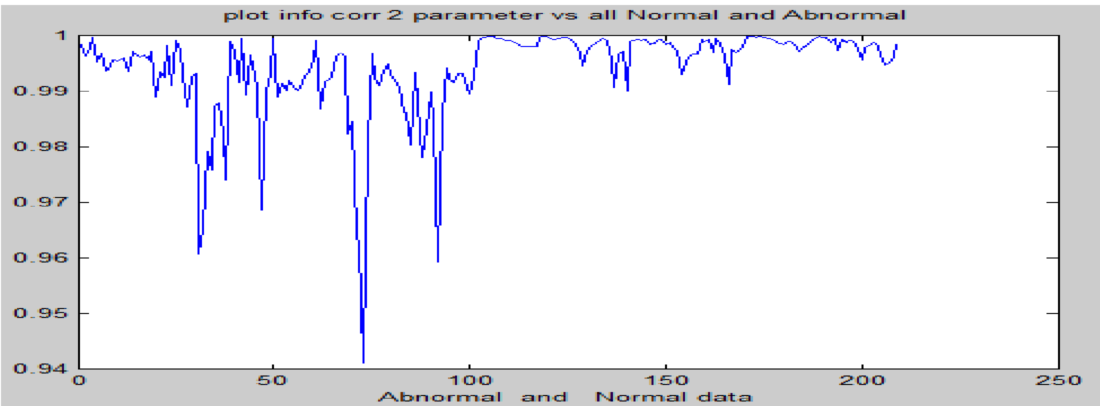

Figure 5. 13 Info-correlation-2 feature for 101 abnormal and 102 normal.

From above figures was selected the best eight feature and used as input to Artificial neural net work.

5.1.2 Result of the Image Processing:

This show and summarized the results of all image processing steps for two images; original image, preprocessing, threshold segmentation, morphological operations and the tumor in image see fig.5.14.

5.1.3Results of Artificial Neural Networks Training:

This is result of Back propagation Artificial neural networks training and performance of training for best eight parameter and random choose different parameter .

A. Result of random parameter:

First ,choose eight random parameter from thirteen Haralick's features to test the performance of Artificial Neural Networks ,the parameter are: Energy(EG), Correlation(CO), Inertia(IN), Entropy(EN), Sum Average(SA), Difference Average(DA), Information measure of correlation-1(IC-1) and Information measure of correlation-2(IC-2) and their performance to detect the tumor is show in fig(4-15) in confusion matrix of networks. And then choose another eight features; Sum Average(SA), Sum Variance(SV), Sum Entropy(SE), Difference Average(DA), Difference Variance(DV), Difference Entropy(DE), Information measure of correlation-1(IC-1)and Information measure of correlation-2(IC-2) and their performance to detect the tumor is show in fig(5-14) in confusion matrix of networks. Finally, choose another eight parameter Energy(EG), Correlation(CO), Inertia(IN), Entropy(EN), Sum Variance(SV), Sum Entropy(SE), Information measure of correlation-1(IC-1) and Information measure of correlation-2(IC-2) and their performance to detect the tumor is show in fig(5-16) in confusion matrix of networks.

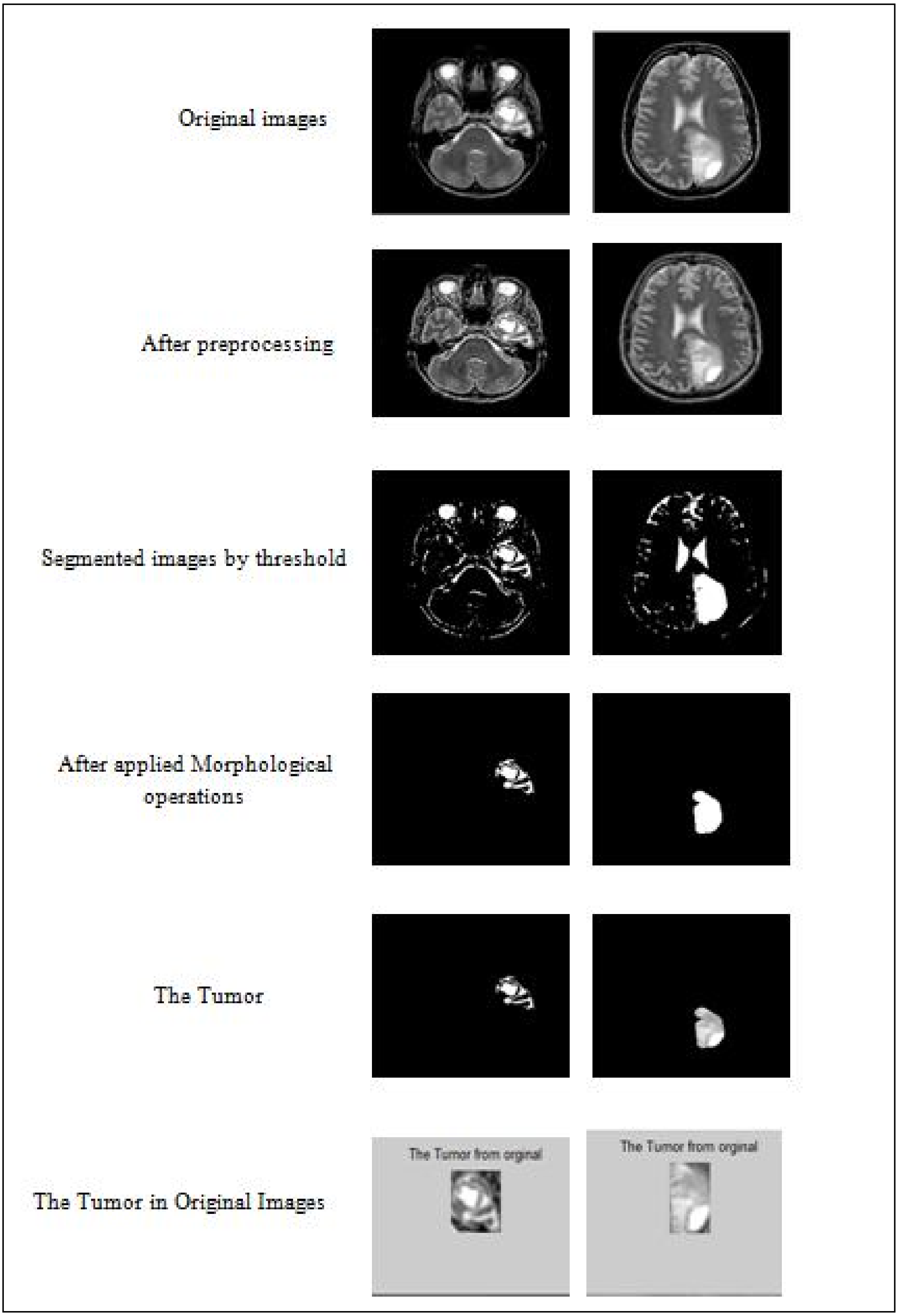

figure 5. 14 steps of region segmentation

B. Result of best parameters:

This is the results of the best eight parameter (features) which used to detect the tumor in this project, the parameter are: Energy(EG), Inertia(IN), Entropy(EN), Inverse Difference Moment(IDM), Sum Variance(SV), Sum Entropy(SE), Difference Variance(DV) and Difference Entropy(DE). The effect of these feature for training process of networks show from fig.5.17 to fig.5.24.

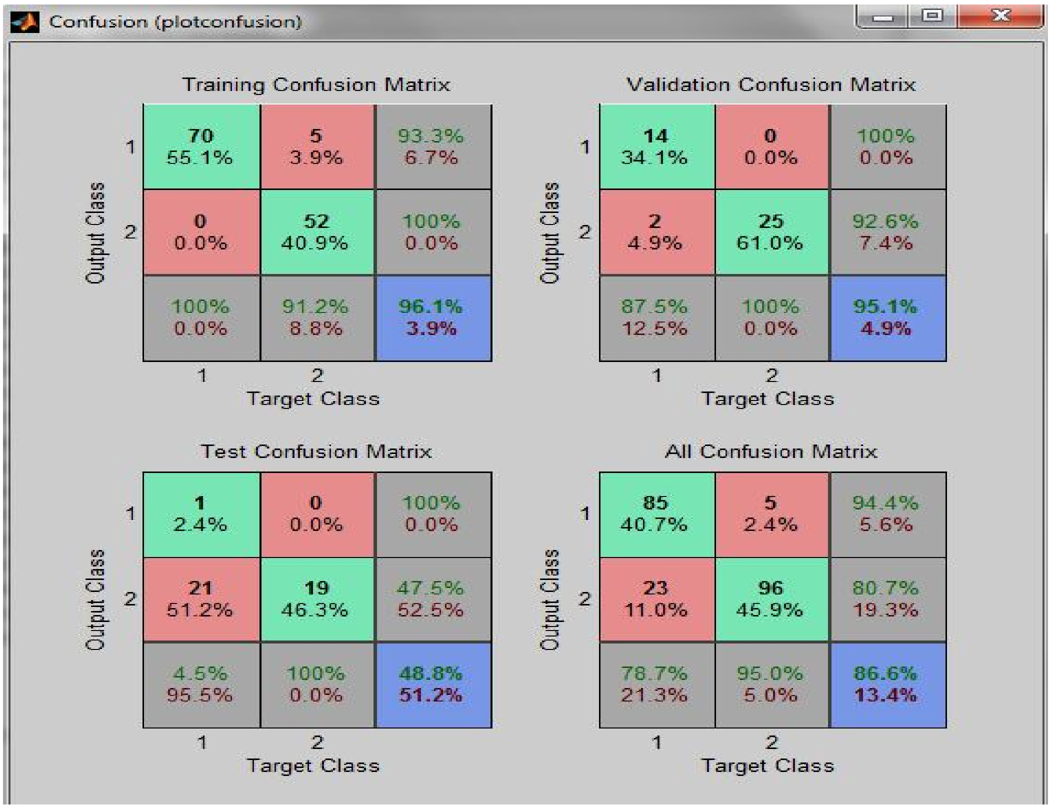

figure 5. 15 confusion matrix of (Energy, Correlation, Inertia, Entropy, Sum Average, Difference Average, Information measure of correlation 1 and Information measure of correlation 2)

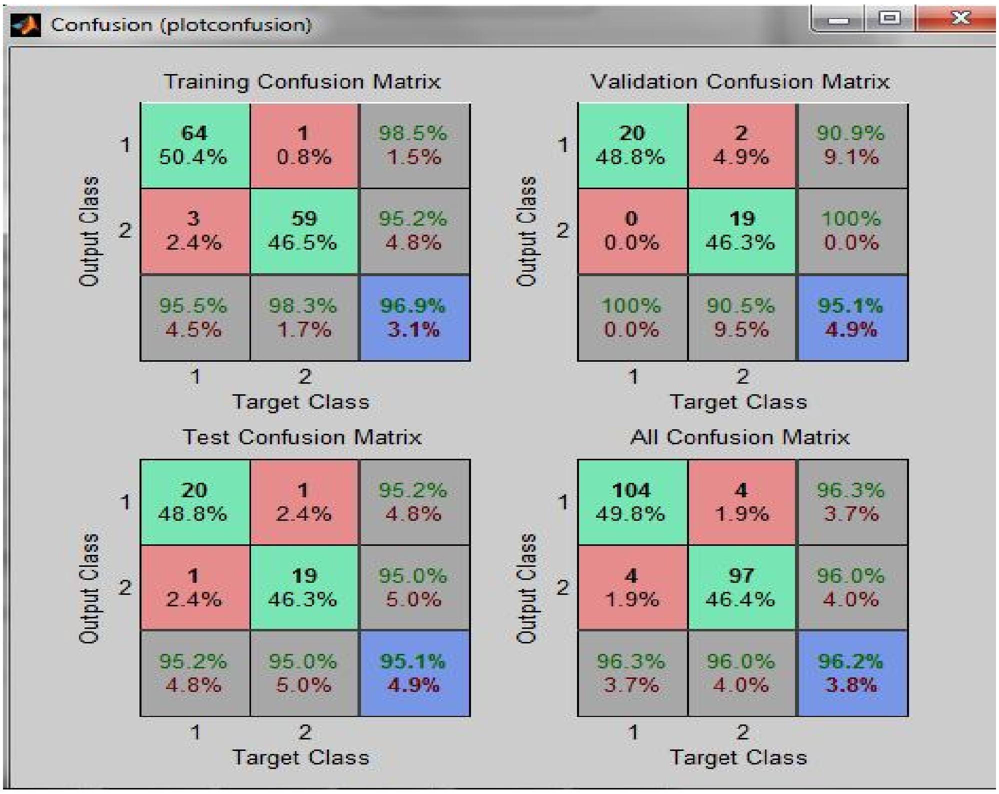

figure 5. 16 confusion matrix of (Sum Average, Sum Variance, Sum Entropy, Difference Average, Difference Variance, Difference Entropy, Information measure of correlation 1,Information measure of correlation 2)

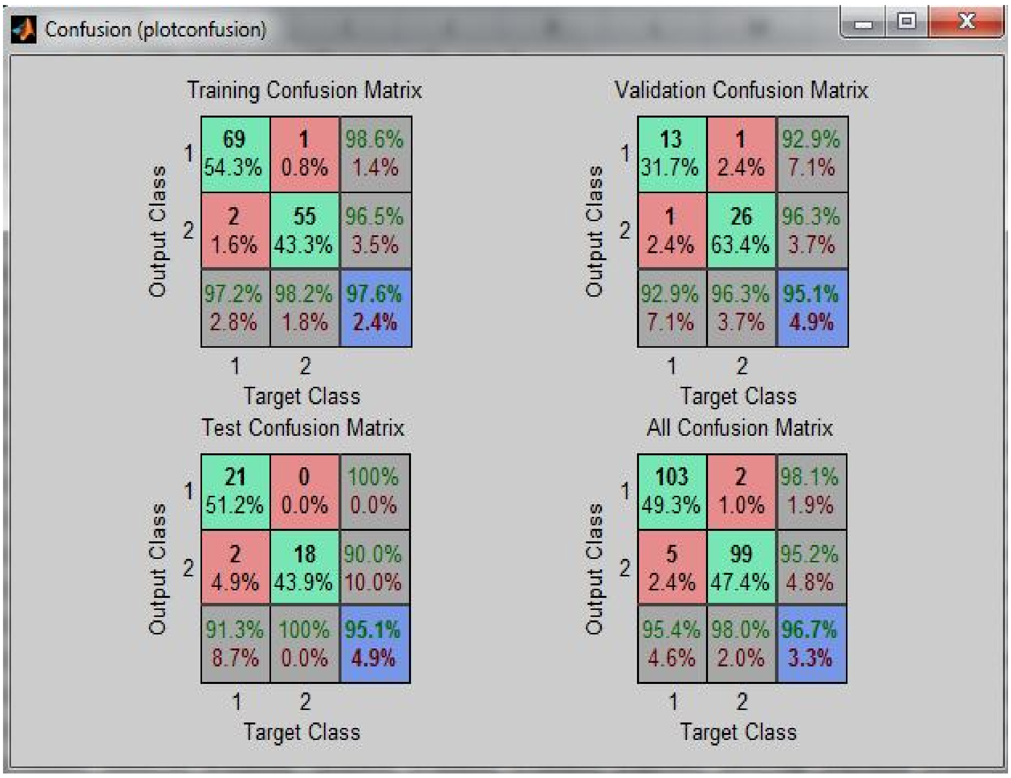

figure 5. 17confusion matrix of (Energy, Correlation, Inertia, Entropy, Sum Variance, Sum Entropy, Information measure of correlation-1and Information measure of correlation-2)

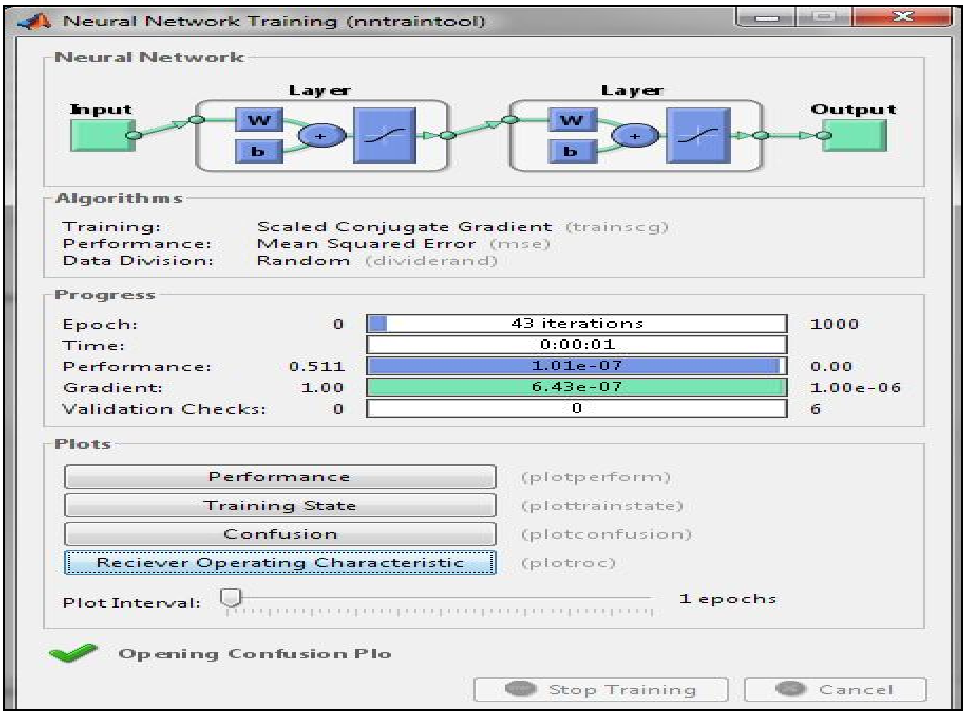

figure 5. 18Architecture of Backpropagation Neural Network Training for best eight feature

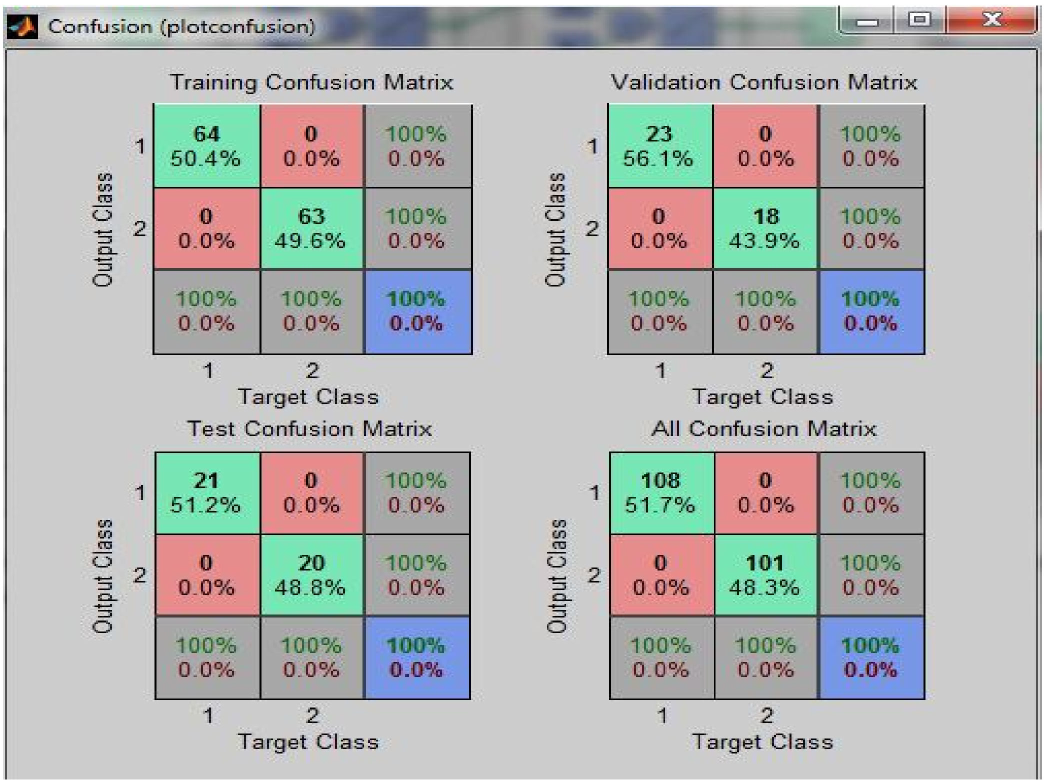

figure 5. 19 confusion matrix of best eight feature

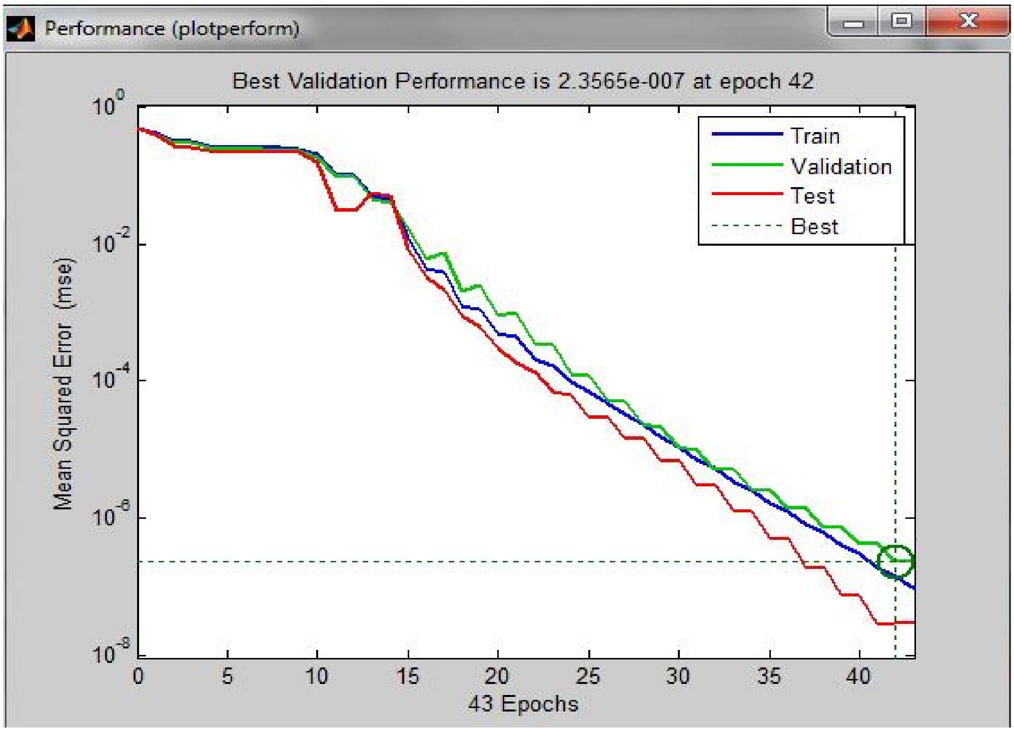

figure 5. 20plot performance of best eight feature

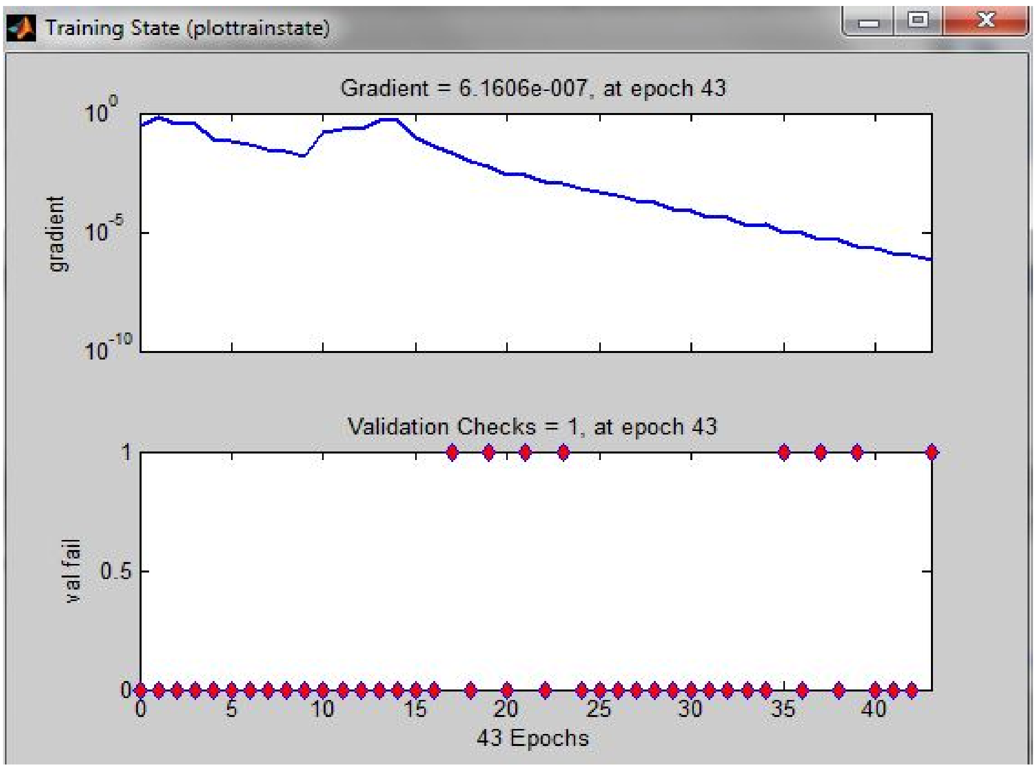

figure 5. 21plot Training State of best eight feature

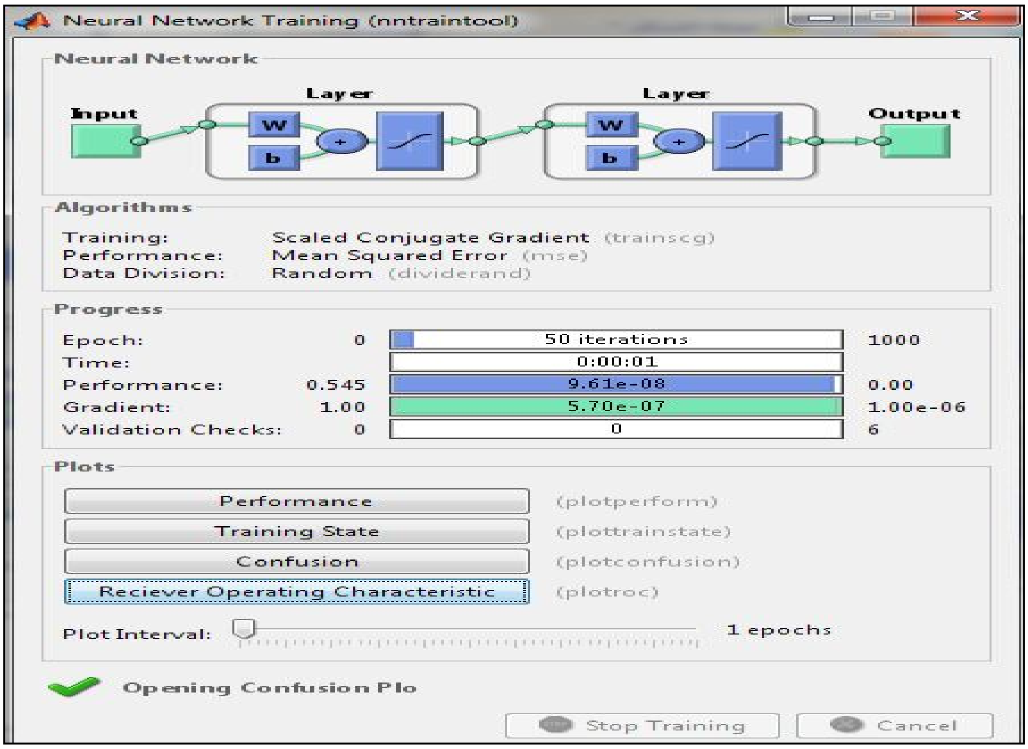

figure 5. 22Architecture of Back propagation Neural Network Training for best eight feature for 300 data.

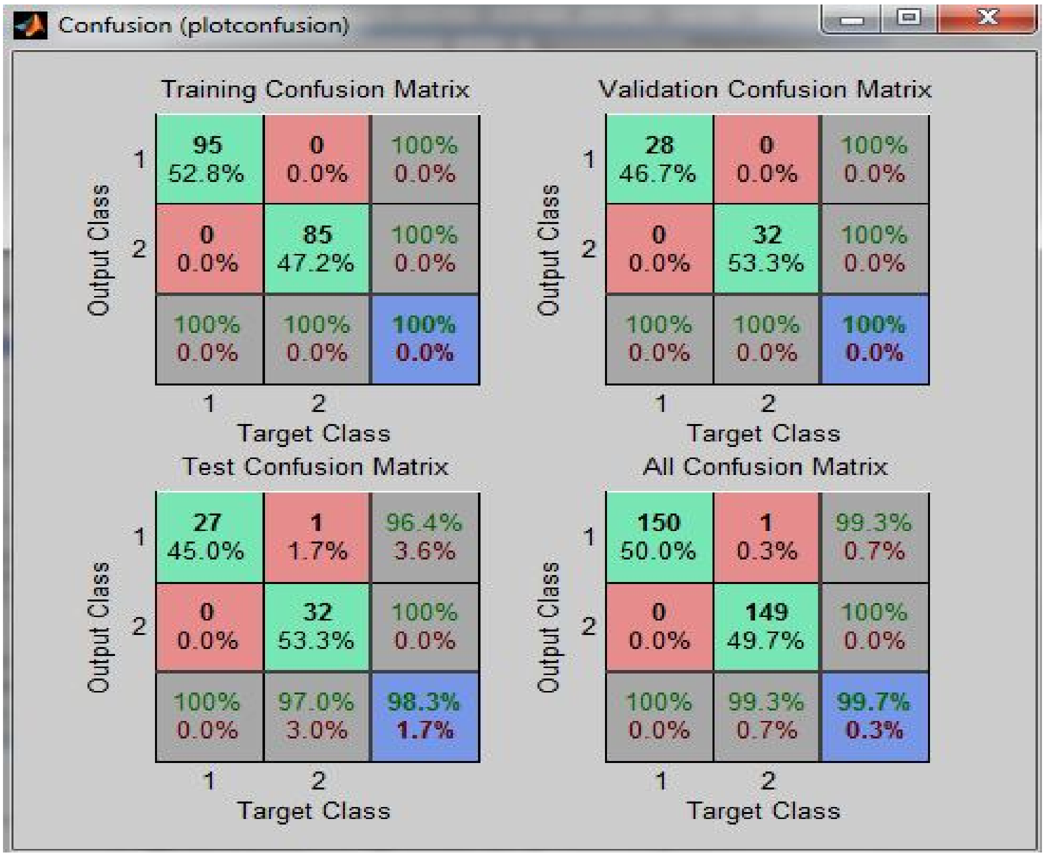

figure 5. 23confusion matrix of best eight feature for 300 data

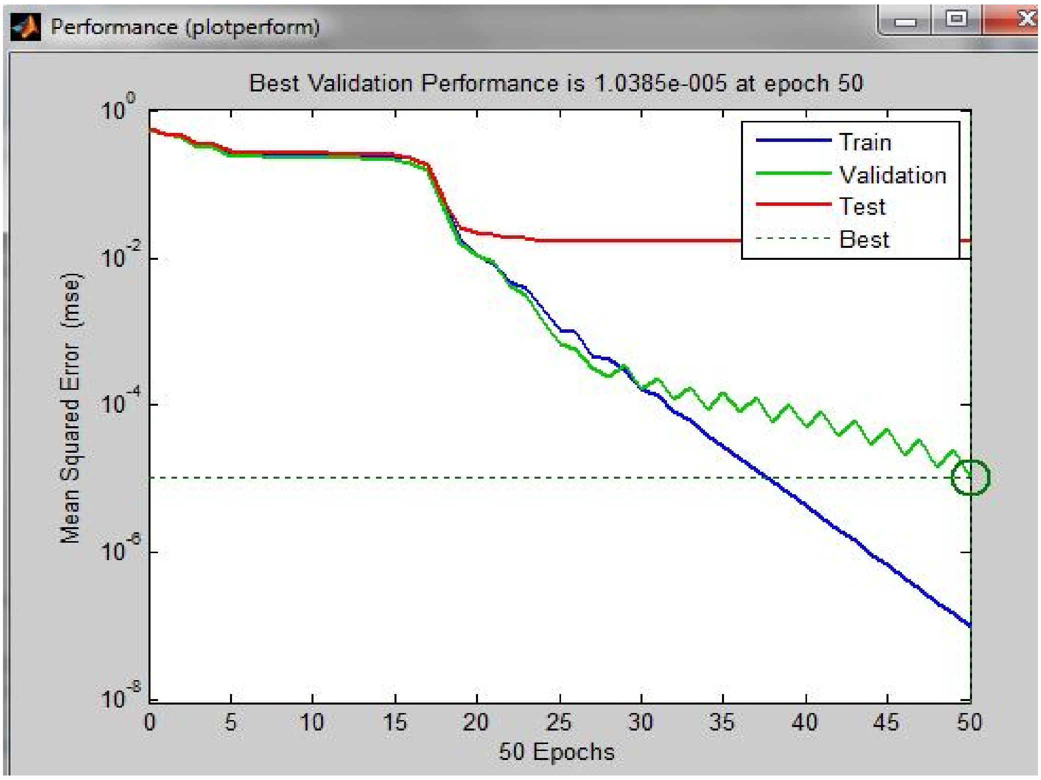

figure 5. 24 plot performance of best eight feature for 300 data.

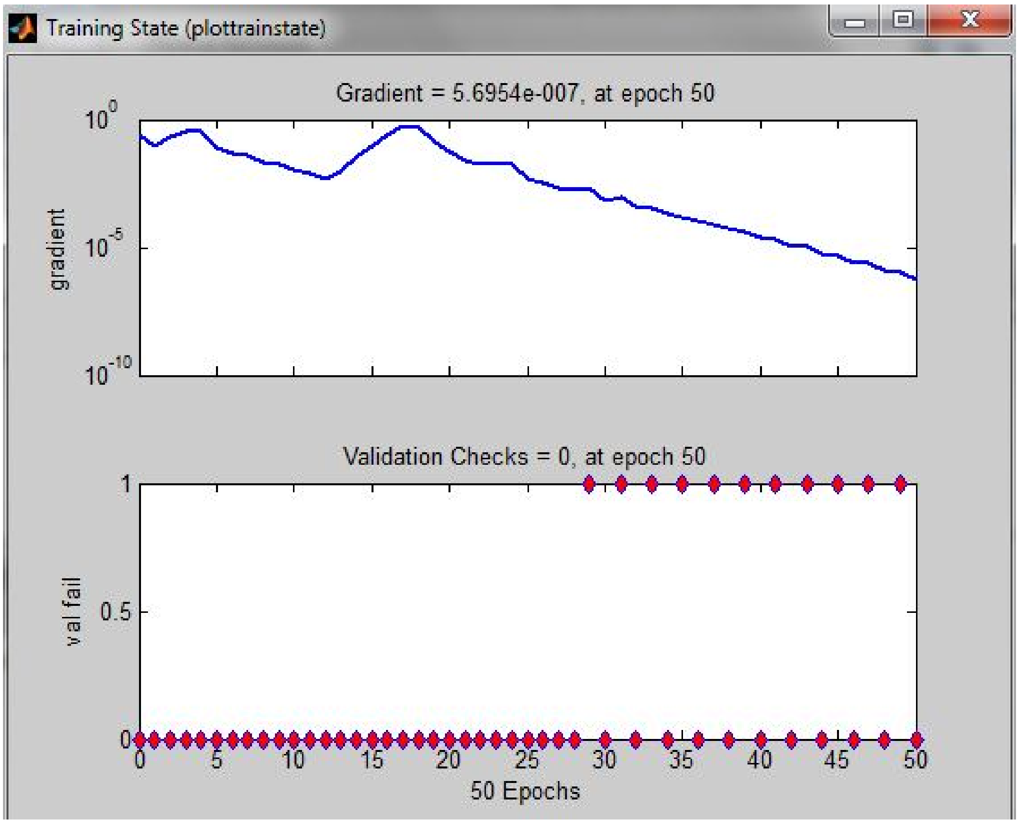

figure 5. 25plot Training State of best eight feature for 300 data.

5.1.3 Results of Graphic User Interface(GUI):

this section presented result of Graphic User Interface(GUI) widow to describe all the proposed algorithm for brain tumor detection from load image to detect the tumor step-by-step.

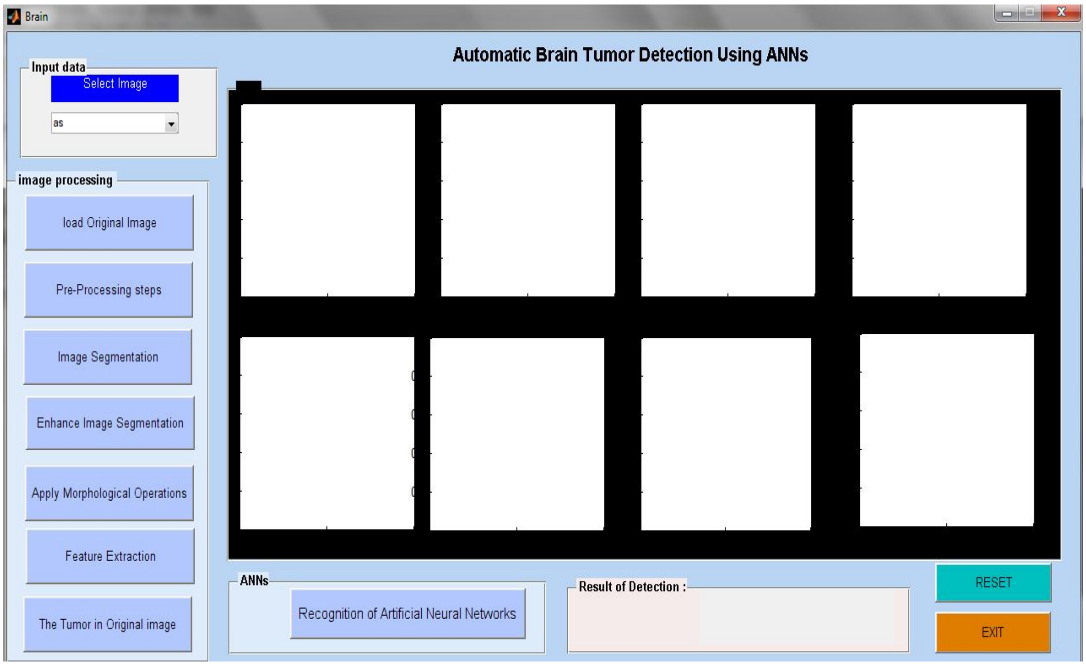

figure 5. 26GUI window for Automatic Brain tumor detection

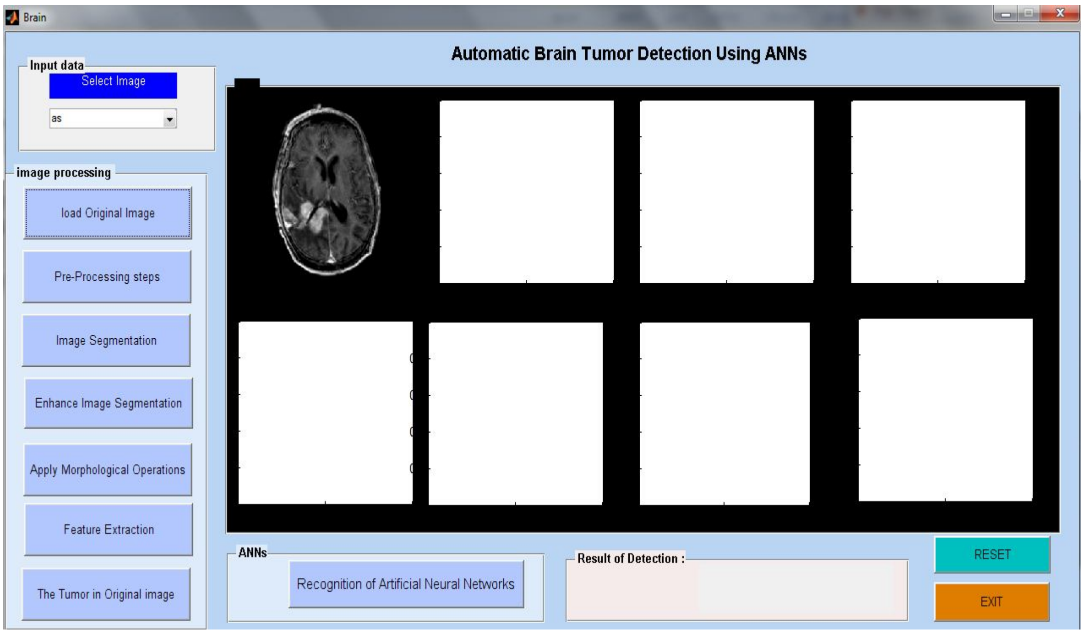

figure 5. 27 Image selector and load Original Image

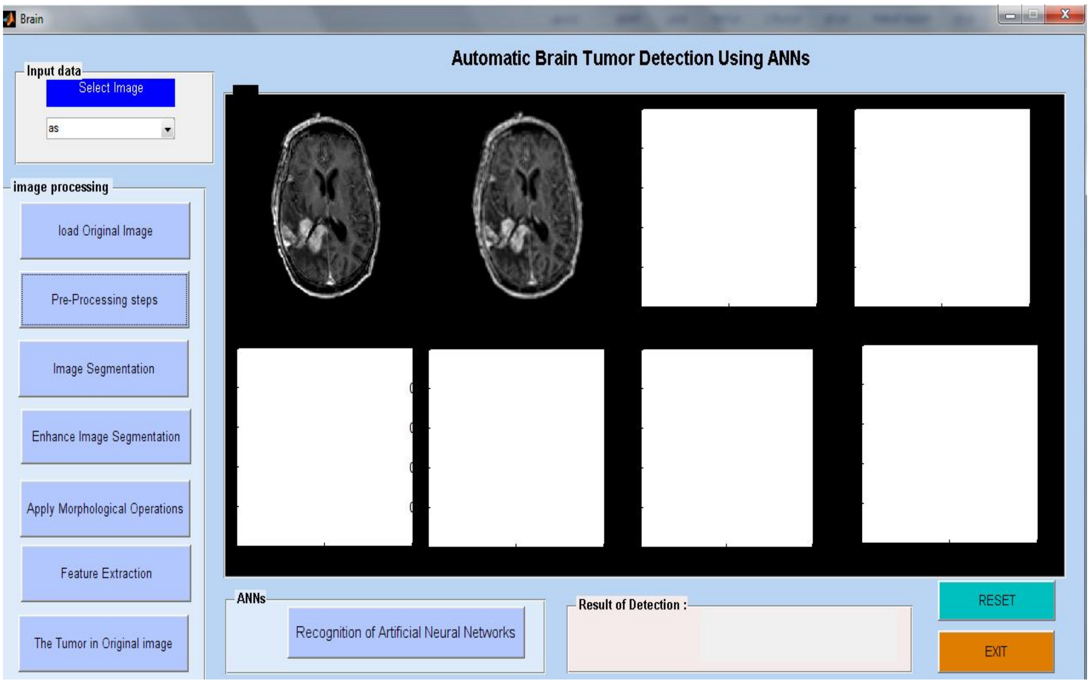

figure 5. 28 Pre- processing of Image

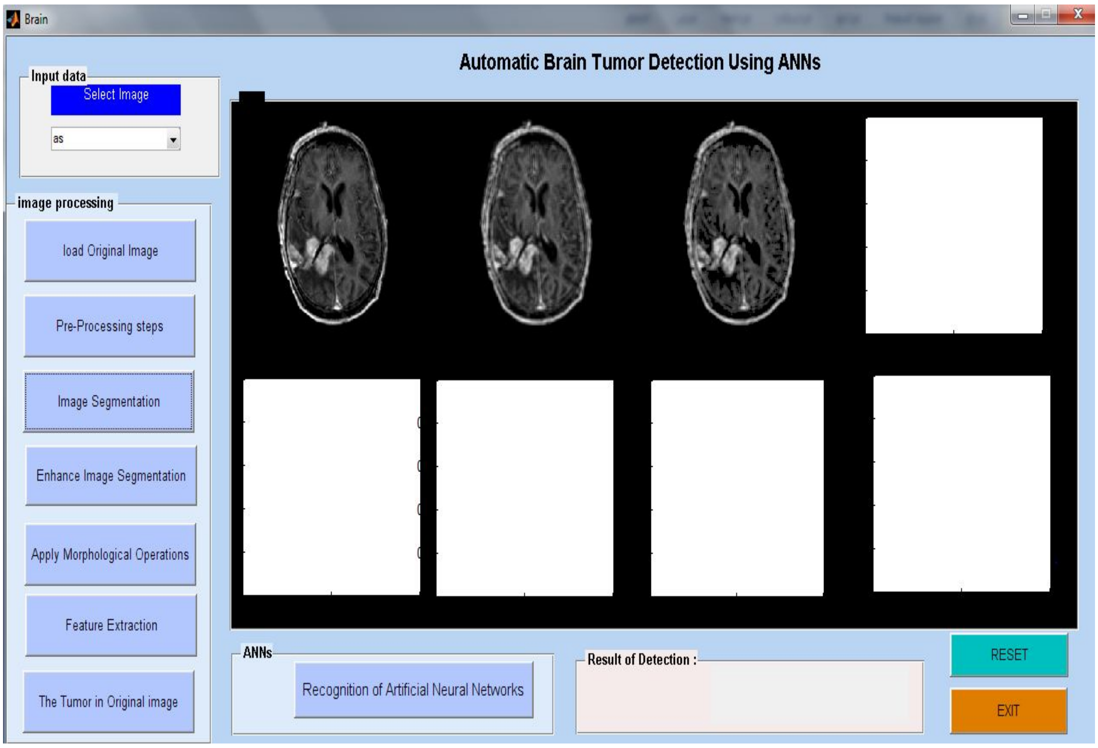

figure 5. 29 Image segmentation

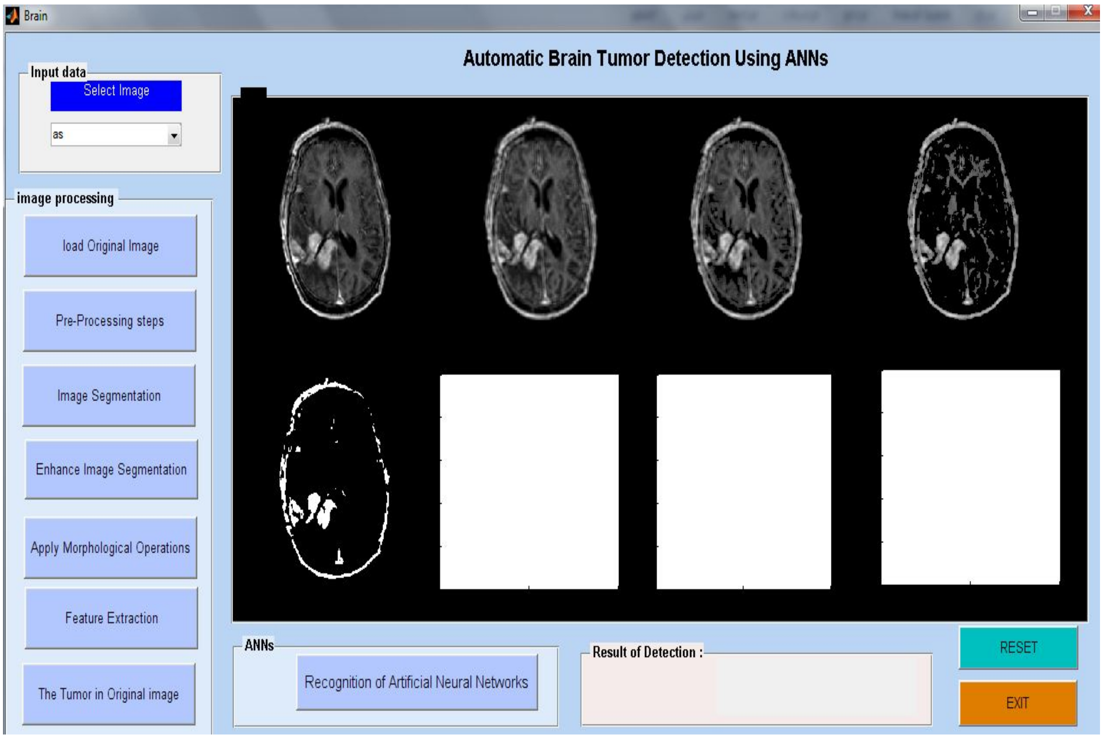

figure 5. 30 Enhance Image segmentation

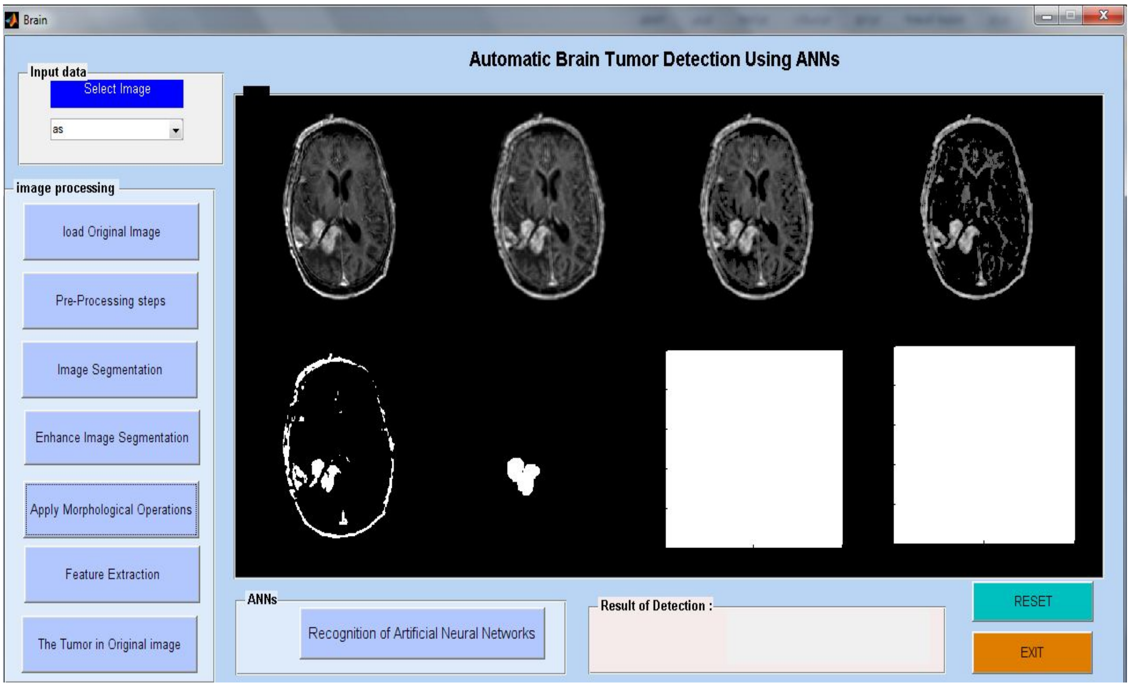

figure 5. 31 Apply Morphological Operation

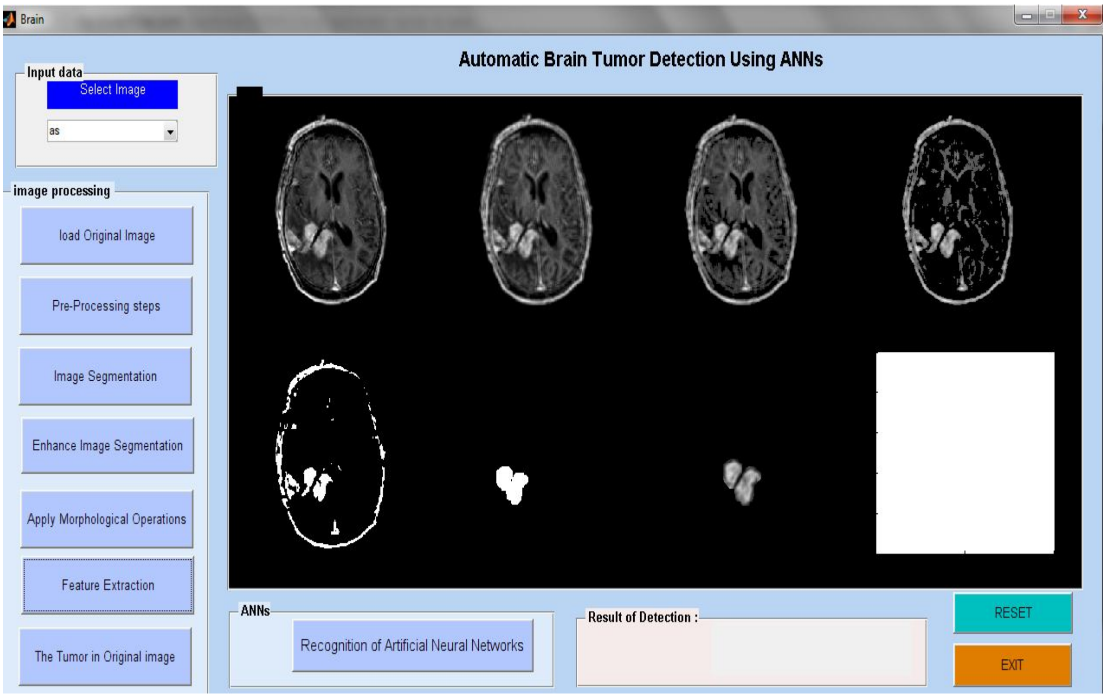

figure 5. 32 Feature Extraction

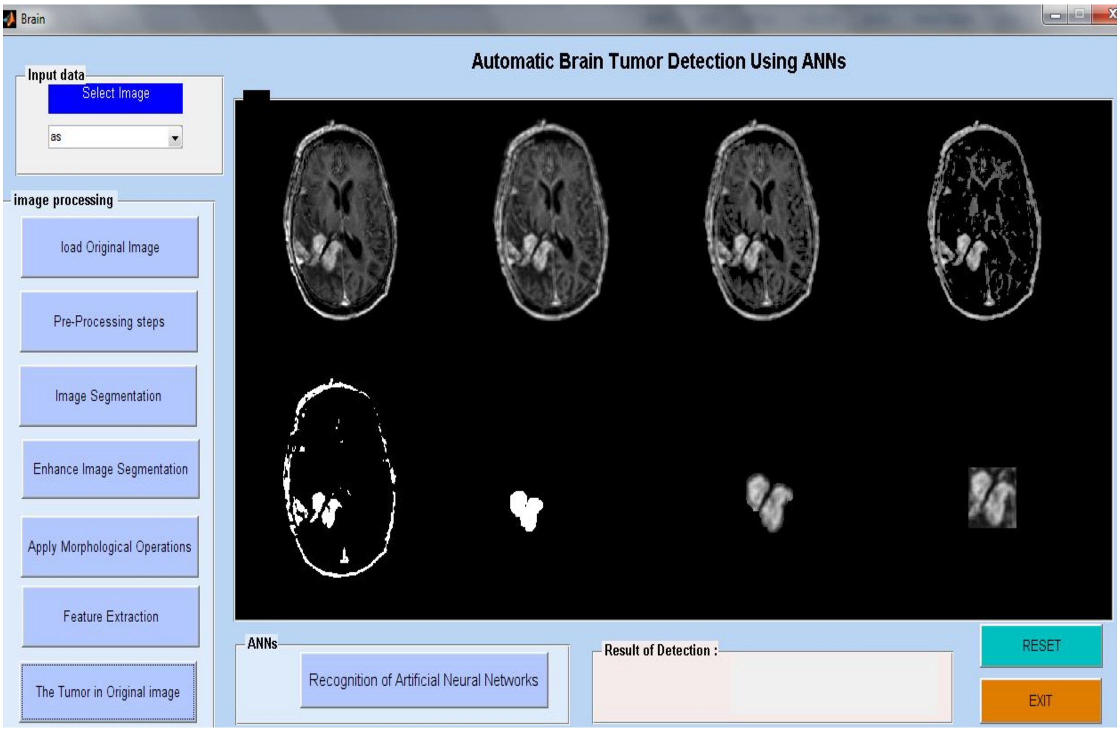

figure 5. 33The Tumor in Original Image

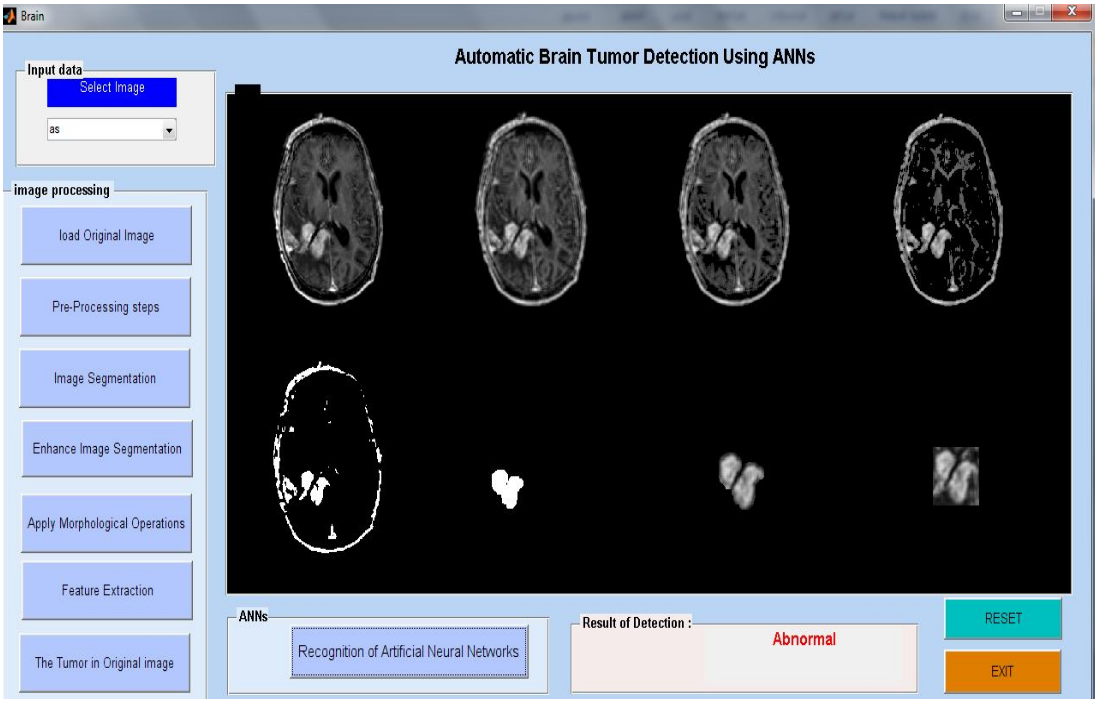

figure 5. 34 The Recognition of ANNs and the Result of Detection

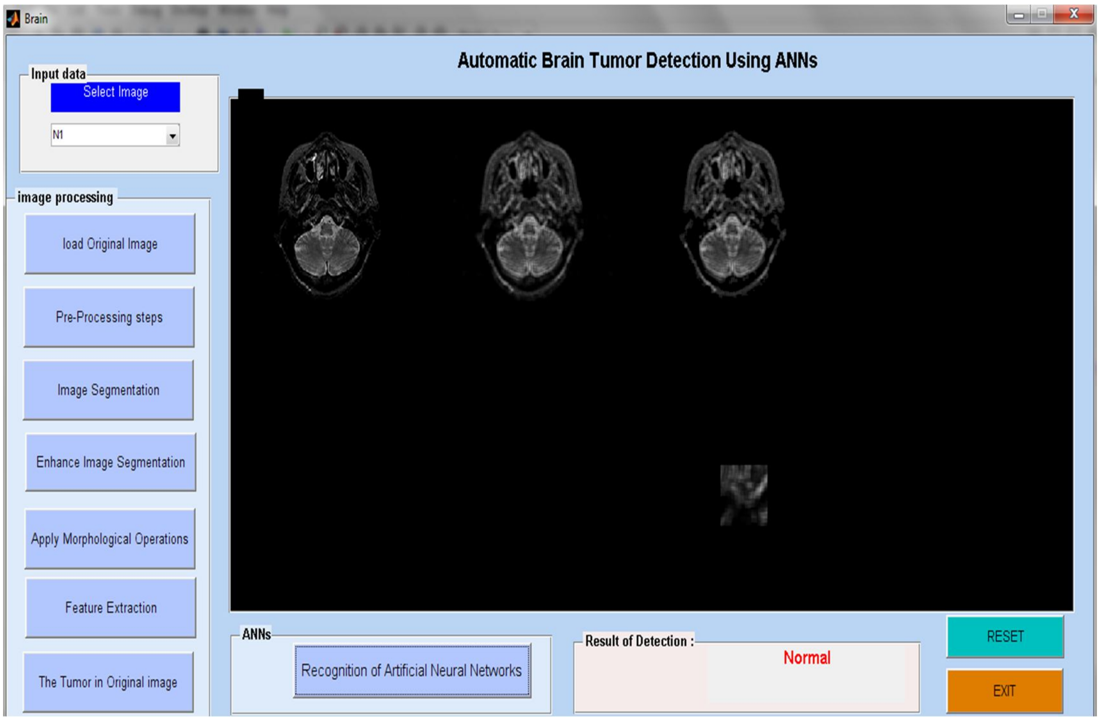

figure 5. 35 The Result of Detection

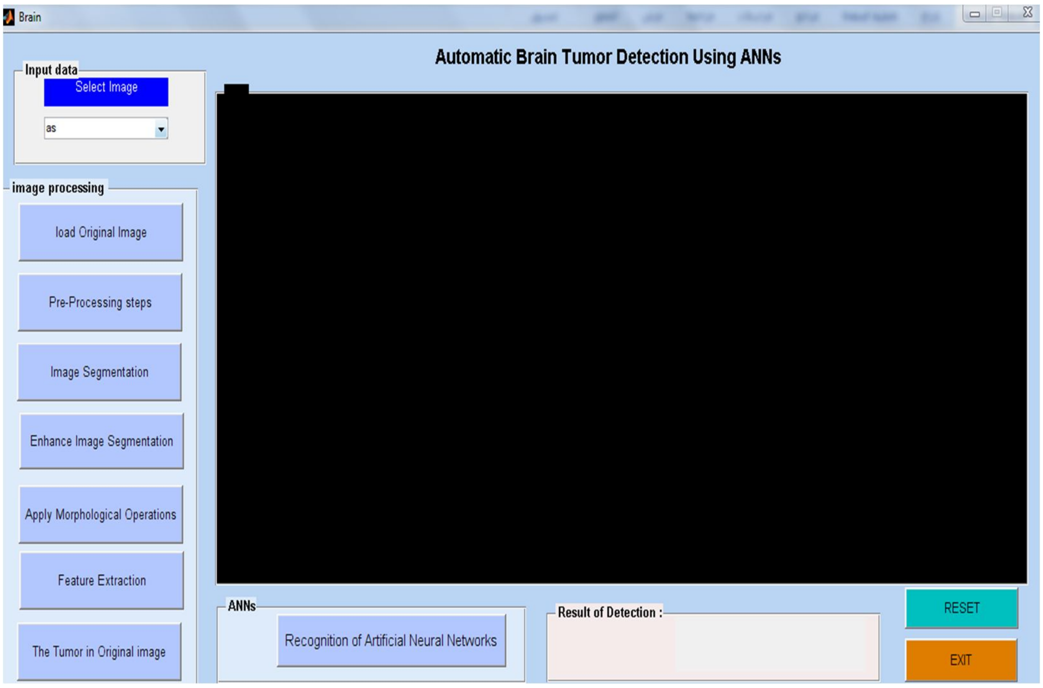

figure 5. 36 The Reset of GUI window

5.1.4 Efficiency of the Results:

The efficient of proposed algorithm can be calculate by predictive values ,There are four predictive values: true positive value (TP), true negative value (TN), false positive value (FN) and false positive value (FP). This used to calculate the performance of proposed algorithm results which applied in MRI images by sensitivity, specificity and accuracy of the system[35].

The calculation for test images (images used for test after training process)show in table (5.1).

Table 5.1: Predictive values (TP, TN, FP and FN) of the system

Statement	Abnormal	Normal	Total
Positive	47(TP)	0(TN)	47
Negative	1(FP)	52(FN)	53
Total	48	52	100

The sensitivity: This is the probability of positive result given that the subject has the disease.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FP}} * 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(37)$$

$$\text{Sensitivity} = \frac{47}{47+1} * 100 = 97.92\%$$

The specificity: This is the probability of negative result given that the subject does not have the disease.

$$\text{Specificity} = \frac{\text{TN}}{\text{FN+TN}} * 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(38)$$

$$\text{Specificity} = \frac{52}{52+0} * 100 = 100\%$$

Accuracy: Accuracy is how close a measured value is to the actual (true) value.

$$\text{Accuracy} = \frac{\text{Numberofcorectdata}}{\text{Numberofalldata}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(39)$$

$$\text{Accuracy} = \frac{99}{100} = 0.99$$

5.2 Discussions:

After collected the database from Whole Brain Atlas, then applied the preprocessing steps, this process effect for in image and change the some in formations of images for this reasons was calculated the mean square error The values of mean square error (MSE) between original images and after applied preprocessing steps for all MRI images database that used in this project are less than 0.3that mean preprocessing does not reduce the information of images.

in section (5.1.1) the results of Haralick's features in plot figures Can be observed some figures like fig(5.1), fig(5.5) fig(5.7) fig(5.8) and fig(5.11), their values versus the abnormal cases(form begging to 101) they have very variation because the tumor has different type of cell which has various intensity in their images; but in the normal cases(from 102 to 203in x axis) the values are homogeneity and have a little variation, that can very easily distinguish between normal and abnormal cases, also in figures: fig (5.3) and fig(5.10) Can be observed the values of abnormal have very variation and some homogeneity in abnormal images, that can easily distinguish between normal and abnormal cases, and in the figures: fig(5.2), fig(5.6), fig(5.9), fig(5.12) and fig(5.15) it difficult distinguish between the normal and abnormal. So the Energy(EG), Inertia(IN), Entropy(EN), Inverse Difference Moment(IDM), Sum Variance(SV), Sum Entropy(SE), Difference Variance(DV) and Difference Entropy(DE) were selected as the best and suitable features to detect the tumor in MRI images.

In section (5.1.3) when the select eight feature randomly contains (just three from suitable features and five from unsuitable features) the performance of network in training state is equal 86.6%in confusion matrix see fig(5.14) and when choose another eight contains(four from suitable and four from unsuitable) the performance of network in training state is equal 96.2% see fig(5.15), and it equal 96.7% for (five from suitable and three from unsuitable) see fig(5.16); but when choose all the suitable eight feature the performance equal 100% see fig(5.18).

Finally from section (5.1.4) evaluate the result by applied 100 cases(52 normal and 48 abnormal) in network after the training process. The proposed algorithm reaches accuracy about 99%, and sensitivity about 97.9%.

Notice that the proposed method and their algorithm gave acceptable results according for it is sensitivity and accuracy percentage and anther methods.

CHAPTER SIX

CONCLUSIONS AND RECOMMENDATIONS

CHAPTER SIX
6.CONCLUSIONS AND RECOMMENDATIONS

6.1Conclusions

This theses 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 Whole Brain Atlas website and its prepared by pre-processing and post-processing operation to make it suitable to detect.

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 dependency matrix(SGLD) of images. Then selected the suitable and best eight features to detect the tumor from thirteen Haralick's features.

For artificial neural networks the feed-forward back propagation neural network with supervised learning was used to classify the images to with or without tumor. And all the best eight features were used as input parameters for back propagation network, then the network was trained and its performance was evaluated.

Finally; the proposed algorithm, which based on the back propagation network has been successfully tested and achieved the best results with accuracy 99%, and sensitivity 97.9%.

And all the results of this study step by step were presented in window of Graphic User Interface(GUI).

The system is designed to be user friendly by creating Graphical User Interface (GUI).The proposed system efficiently classifies the MRI brain tumor images. The tumor is isolated from the MRI brain images by using integrated image processing algorithm based on a modified method texture detection algorithm spatial gray level dependency matrix(SGLD) of images using MATLAB.

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:

Diagnosis of brain tumors is dependent on the detection of abnormal brain structure, but the successful treatment of brain tumors depends on a number of factors such as the type, location and size of the tumor. As diagnosis tumor is a complicated and sensitive task; therefore, accuracy and reliability are always assigned much importance.

The algorithm designed in this study is proposed for brain tumor classification from MRI data by means of texture analysis based on GLCM to train the ANNs. In this work study a suitable artificial neural network classifier is designed used back propagation algorithm to identify the brain tumors with good accuracy.

The following recommendations are suggested :

- There is need for automated classification of brain tumor built in modern imaging technology, and it is vital to develop a system with novel algorithms to detect brain tumor efficiently at early stages.
- 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.
- Develop the proposed algorithm to classify abnormal feature into benign and malignant tumor or according to type of brain tumors.
- Design auto dynamic brain tumor detection system, detect the tumor according to its size ,direction and shape in image.
- The system can further be further used for classification of images with different pathological condition, types and disease status by using

other types of image modalities (e.g. CTS canner, PET, MRS, and mammogram) for cancers classification.

REFRENCES

[1] NCI., " General Information About Adult Brain Tumors. NCI. ," National Cancer Institute2014-04-14. Retrieved 8 June 2014.

[2] S. Shweta Jain, "ANN Approach Based On Back Propagation Network and Probabilistic Neural Network to Classify Brain Cancer," International Journal of Innovative Technology and Exploring Engineering (IJITEE), vol. 3, August 2013.

[3] T.-h. Kim et al. (Eds.), Brain Tumor Detection Using MRI Image Analysis. Springer-Verlag Berlin Heidelberg,: UCMA, 2011.

[4] N. N. Gopal, Karnan, M.,, " Diagnose brain tumor through MRI using image processing clustering algorithms such as Fuzzy C Means along with intelligent optimization techniques," presented at the Computational Intelligence and Computing Research (ICCIC), 28 - Dec. 2010.

[5] S. a. E. N. Sharma, " Brain Tumor Detection and Segmentation Using Artificial Neural Network Techniques," International Journal of Engineering Sciences & Research Technology, August 2014.

[6] Geoff Dougherty, Digital Image Processing for Medical Applications. California State University, Channel Islands,: Cambridge University Press, 2009.

[7] http://www.neurosolutions.com/products/ns/whatisNN.html?utm_campaign =Newsletter&utm_medium=Email&utm_source=ConstantContact. Available: http://www.neurosolutions.com/products/ns/whatisNN.html?utm_campaign= Newsletter&utm_medium=Email&utm_source=ConstantContact.

[8] QeetharaKadhim Al-Shaye, "Artificial Neural Networks in Medical Diagnosis," IJCSI International Journal of Computer Science Issues,, vol. 8, March 2011.

[9] R. Dybowski and V. Gant, Clinical Applications of Artificial Neural Networks: Cambridge University Press, 2007.

[10] I. MathWorks, MATLAB: the language of technical computing. Desktop tools and development environment, version 7 vol. 9: MathWorks, 2005.

[11] Isabelle Guyon and Andr´eElisseeff, "An Introduction to Feature Extraction," ed USA.

[12] Andrzej Materka and Michal Strzelecki, "“Texture Analysis Methods – A Review”, ," Technical University of Lodz, Institute of Electronics COST B11 report, Brussels 1998.

[13] V. P. G. R. a. Dr.S.Palani, "Brain Tumor Mri Image Classification With Feature Selection And Extraction Using Linear Discriminant Analysis."

[14] R. J. D. a. R. S. Khule, "Brain Tumor Detection Using Artificial Neural Network Fuzzy Inference System (ANFIS)," International Journal of Computer Applications Technology and Research, vol. 3, pp. 1 50 - 1 54, 2014.

[15] P.B.Nikam and V.D.Shinde, "MRI Brain Image Classification and Detection Using Distance Classifier Method in Image Processing," International Journal of Engineering Research & Technology (IJERT) vol. 2, 2013.

[16] N. C. Institute. (March). Brain Tumors. Available: http://www.cancer.gov/publications

[17] National Cancer Institute (NCI), "Adult Brain Tumors Treatment " NCI Publications Locator,February 13 -2015.

[18] K. M. Michal Kvet, "Brain Tumour Detection," Journal of Biomedical Engineering and Technology, 2013.

[19] www.cancercouncil.com.au. (2011). Understanding Brain Tumours. Available: www.cancercouncil.com.au

[20] American Brain Tumor Association (2010). Brain Tumor Primer” a comprehensive introduction to brain tumors (9th edition ed.). Available: http://neurosurgery.mgh.harvard.edu/abta/abta_braintumorprimer.pdf

[21] W. B. M. Ober, Frederic,, Fundamentals of anatomy &physiology San Francisco: : Pearson Benjamin Cummings, 2006.

[22] http://www.nhs.uk/conditions/MRIscan/Pages/Introduction.aspx. Available: http://www.nhs.uk/conditions/MRIscan/Pages/Introduction.aspx

[23] P. D. a. R. C. S. Mark A. Brown, M.D,, MRI basic principles and applications. United States of America,, 2003.

[24] Robin N. Strickland, Image-Processing Techniques for Tumor Detection. New York Marcel Dekker,, 2002.

[25] QeetharaKadhim Al-Shayea "Artificial Neural Networks in Medical Diagnosis," IJCSI International Journal of Computer Science Issues,, vol. 8, 2011.

[26] F. Rosenblatt Principles of Neurodynamics. New York, NY,: Spartan,, 1962.

[27] G Vijay Kumar and Dr GV Raju, "Biological Early Brain Cancer Detection usingAatificialNeuralNetwork," International Journal on Computer Science and Engineering, vol. 02, 2010.

[28] RaoufN.G.Naguib and V. Sherbet, Artificial Neural Networks in Cancer Diagnosis prognosis and patient management. New York,: CRC press LLC, 2001.

[29] Rafael C. Gonzalez, Digital Image Processing, Second Edition ed. United States of America: University of Tennessee, 2001.

[30] http://www.med.harvard.edu/aanlib/home.html. Available: http://www.med.harvard.edu/aanlib/home.html

[31] R. S. PankajSapra, ShivaniKhurana,, "Brain Tumor Detection Using Neural Network," International Journal of Science and Modern Engineering (IJISME), vol. 1, August 2013.

[32] Fatehia B.Garma and MawiaA.Hassan, "Calssification of Breast Tissue as Noraml or Abnormal Based on Texture Analysis of Digital Mammogram," journal of medical imaging and health informatics, vol. 4, pp. 1-7, 2014.

[33] K. S. R. Haralick, I. Dinstein, , "Textural Features for Image Classification," IEEE Trans. on Systems, Man and Cybernetics SMC, vol. 3, pp. 610-621, 1973.

[34] T. P. Vogl, J.K. Mangis, A.K. Rigler, W.T. Zink, and D.L. Alkon, , "Accelerating the convergence of the backpropagation method," Biological Cybernetics, vol. 59, pp. 257-263,, 1988.

[35] Wayne W. Daniel, Biostatistics A Foundation for Analysis in the Health Sciences. the United States of America, : John Wiley & Sons, Inc,, 2009.

APPENDIX

APPENDIX

Features of The Data:

This section present the thirteen features of MRI images; normal and abnormal which used in this project. These features calculated by using the haralick’s equations .

The Haralick's texture features are: Energy(EG), Correlation(CO), Inertia(IN), Entropy(EN), Inverse Difference Moment(IDM), Sum Average(SA), Sum Variance(SV), Sum Entropy(SE), Difference Average(DA), Difference Variance(DV), Difference Entropy(DE), Information measure of correlation-1(ICO-1) and Information measure of correlation-2(ICO-2) in the table below:

Table(A1) show features of the data:

relation	**inertia**	**entropy**	**inverse_ diff**	**sum_ avg**	**sum_ var**	**sum_ entropy**	**diff_ avg**	**diff_ var**	**diff_ entro**
67377	353.2008	7.857444	0.421503	150.9231	21300.12	6.090211	10.65647	239.6404	4.260
53873	424.3123	7.994863	0.444315	143.2297	17973.11	5.963474	10.1159	321.9809	4.144
63207	381.2427	6.86744	0.504494	125.6988	20342.4	5.468478	9.23083	296.0345	3.807
60478	354.6147	8.701918	0.306169	170.4589	17590.51	6.992285	11.88918	213.2622	4.718
21141	1303.364	8.276211	0.384688	253.5556	31752.26	6.191205	13.02402	1133.739	4.140
28928	1130.164	8.832805	0.355841	298.1532	30673.21	6.604384	11.98146	986.6084	4.151
29238	1035.757	9.054375	0.336796	295.846	28238.49	6.551098	11.82258	895.9832	4.246

31965	1010.728	8.857339	0.356725	273.8579	28701.43	6.413715	11.52113	877.9917	4.164
32323	1284.599	8.295219	0.444003	289.9926	36678.14	6.226385	12.22963	1135.035	3.974
75892	2172.966	8.14386	0.420268	356.3273	32844.31	6.216625	14.62614	1959.042	3.941
36726	1994.23	8.295223	0.431285	291.9628	33216.41	6.345547	13.7749	1804.482	3.855
39937	2204.445	8.73705	0.328104	274.6802	25340.3	6.635564	16.72617	1924.68	4.294
9682	1705.129	7.203734	0.341514	191.9353	15079.25	5.646381	17.15294	1410.906	4.113
03366	4310.655	5.98136	0.305165	215.5818	24753.13	5.119952	34.36364	3129.795	4.713
5262	2123.305	6.60475	0.455259	175.7051	26690.68	5.339633	19.66061	1736.766	4.207
7503	1993.014	5.492009	0.552423	153.8472	29902.93	4.637545	17.625	1682.373	3.716
92911	1865.762	5.482298	0.554786	161.8681	32979.44	4.577129	16.90972	1579.823	3.687
30894	2089.7	6.192996	0.517892	179.8403	33000.16	4.997392	17.46528	1784.664	3.864
46541	2312.652	7.730682	0.408296	207.7724	27827.74	6.082953	19.5813	1929.224	4.476
33709	1877.376	5.382732	0.596449	147.9497	30410.13	4.328599	14.10884	1678.316	3.276
93552	1745.739	6.14391	0.541732	164.0605	31054.11	4.869684	14.87171	1524.571	3.682

63527	2514.547	5.296759	0.586436	156.535	34335.86	4.347866	17.21197	2218.295	3.424
30456	3063.201	7.248711	0.413011	219.2785	33071.32	5.877562	21.94919	2581.434	4.363
53366	2172.606	3.962175	0.682621	112.7903	27460.53	3.432222	14.2711	1968.942	2.755
96674	3988.677	7.577249	0.317548	302.5955	35245.6	6.272407	25.65	3330.755	4.714
30302	5071.652	7.092879	0.436851	315.068	41097.58	5.845971	26.28	4381.014	4.097
11372	1994.267	7.211692	0.48062	258.0375	43008.89	5.469697	13.03034	1824.477	3.694
19333	1779.775	7.65417	0.424114	282.1367	42346.79	5.580723	12.23741	1630.021	3.786
10557	1695.283	7.919752	0.405232	287.6129	36212.24	5.865389	11.96714	1552.07	3.857
41185	1132.337	7.430698	0.491615	218.6462	37372.83	5.510154	9.756274	1037.152	3.617
41389	1283.913	4.704898	0.698464	154.0567	42527.08	3.542404	7.753602	1223.795	2.395
25688	1839.066	5.535792	0.629375	197.2118	47656.6	4.12932	10.2712	1733.569	2.763
19178	1780.505	5.864061	0.618783	181.634	42279.63	4.413766	10.67571	1666.534	2.961
22927	1451.174	5.404111	0.652219	151.2976	36205.91	4.086326	9.490813	1361.098	2.785
26069	1204.29	7.163713	0.517913	187.109	31374.32	5.247731	11.18789	1079.121	3.693
04474	1308.607	7.875332	0.401689	225.8683	26089.23	5.662972	13.31003	1131.45	4.211
2574	1019.796	7.180484	0.484896	194.7478	26445.62	5.181381	10.19259	915.907	3.707

35908	770.1562	5.965998	0.58675	141.3528	23262.58	4.365715	7.949384	706.9635	3.122
64245	433.6701	8.798076	0.341549	210.6479	23824.28	6.824446	10.30617	327.4529	4.349
75944	397.8792	8.325381	0.433778	209.586	32681.31	6.233424	9.256824	312.1905	4.132
71549	436.7003	7.027107	0.547274	150.2606	30261.72	5.201376	9.606435	344.4167	3.688
20956	2381.03	8.773851	0.352168	151.1808	24216.18	6.947204	19.23654	2010.985	4.699
78042	383.3465	6.722754	0.588114	150.0409	34533.11	4.951086	8.510052	310.9255	3.437
47546	3321.306	6.795283	0.48	227.692	40249.89	5.485563	18.83152	2966.68	3.715
73963	353.4009	6.385977	0.587379	130.9111	26792.52	4.838327	7.683842	294.3595	3.332
75574	291.6182	5.826907	0.631859	112.0201	23586.47	4.434785	6.6331	247.6202	3.047
74237	211.8578	3.978108	0.766448	66.45663	16234.53	3.039448	4.64163	190.3131	2.169
69934	322.4451	5.616535	0.642168	101.7963	21126.74	4.302184	7.083333	272.2715	3.022
75688	258.2506	6.588857	0.57746	118.6117	20986.82	4.962112	6.962712	209.7712	3.347
68684	337.9308	8.194193	0.382076	167.8372	21244.07	6.60113	9.435897	248.8946	4.220
18882	1549.714	5.652639	0.604135	166.2039	36659.3	4.503201	14.21503	1347.647	3.307

28329	1446.463	6.220716	0.579018	182.894	38917.73	4.871191	13.82467	1255.342	3.444
44549	1384.528	6.269386	0.597535	220.1633	48552.69	4.839176	11.82833	1244.618	3.279
26805	1987.284	5.429961	0.648911	282.8615	52313.46	4.449988	12.38636	1833.862	2.911
40768	1599.12	6.5126	0.591015	283.8487	52396.41	5.048738	11.96333	1455.999	3.326
40145	1610.994	6.526703	0.591642	261.219	52218.86	5.020628	11.05487	1488.784	3.221
2367	2014.527	6.335372	0.595351	279.7601	50770.05	4.966682	13.26867	1838.469	3.262
36276	1715.504	5.495088	0.642861	295.1981	52125.94	4.516075	12.43499	1560.876	3.030
37133	1624.461	6.036654	0.603473	284.4571	50055.11	4.828368	12.10431	1477.946	3.221
26133	1794.332	6.809375	0.51305	248.1095	46788.2	5.40305	13.85405	1602.398	3.700
35638	2558.558	7.857855	0.301397	276.1299	28574.74	6.488156	19.78788	2166.998	4.454
32097	1030.223	5.420438	0.57865	117.4338	16445.61	4.39099	11.52941	897.2957	3.268
22371	972.2249	6.328948	0.539711	143.5921	24075.73	4.968061	11.82463	832.4031	3.466
07872	1253.207	6.783625	0.496827	155.6746	25952.68	5.280207	15.04891	1026.737	3.855
27994	929.9062	6.765401	0.515254	156.7705	24898.54	5.202526	11.69115	793.2233	3.637
55988	420.3192	7.96486	0.439517	158.8302	18679.76	6.031067	9.077526	337.9177	3.995

51136	458.2464	8.172458	0.413358	160.919	18297.85	6.208313	9.783116	362.537	4.103
59689	335.1115	7.254878	0.476028	138.1509	16291.4	5.611329	7.798766	274.2908	3.706
45509	1062.667	6.22735	0.57505	181.0815	37940.5	4.60616	9.73501	967.897	3.290
16683	1624.194	6.391855	0.550244	190.1915	37364.15	4.827042	12.30506	1472.779	3.429
41197	1085.645	5.286329	0.648285	150.7803	35839.01	3.890654	8.824044	1007.782	2.838
22643	1277.493	4.362321	0.718614	119.5841	31750.91	3.358767	8.703869	1201.736	2.435
3197	978.3502	3.337441	0.794347	92.37144	27783.9	2.602533	6.125656	940.8265	1.868
31135	1180.33	7.179182	0.512689	179.5975	33099.11	5.1673	14.12403	980.8423	3.923
93363	1645.857	7.249288	0.437866	223.5276	29222.64	5.746061	13.66129	1459.226	3.837
09156	1879.127	6.300587	0.568814	195.5939	39491.43	4.917977	11.75565	1740.932	3.248
57778	561.5244	6.62878	0.552864	147.67	26037.05	5.020359	9.683833	467.7478	3.634
58093	578.3675	6.885804	0.516619	161.3172	27023.91	5.25912	9.865672	481.0361	3.777
45521	777.8223	7.169313	0.478622	181.1964	27777.3	5.493862	11.06964	655.2853	3.906
56354	647.3499	6.342946	0.569193	161.5224	29016.63	4.916855	8.397347	576.8345	3.317
20338	1199.264	8.286739	0.394271	229.2746	28909.49	6.091289	13.56056	1015.375	4.310

35476	949.1773	8.218878	0.417378	220.2951	28471.51	5.952656	11.9696	805.9061	4.210
92957	1680.534	7.961188	0.428314	227.6152	29718.62	5.784991	13.47468	1498.966	3.943
36796	1711.779	8.537333	0.379639	250.0907	28530.57	6.12752	14.70214	1495.626	4.262
31115	2111.393	6.374322	0.545607	181.8083	33408.62	4.831982	14.70625	1895.119	3.491
77402	1981.244	7.663631	0.430432	231.6578	30339.71	5.830119	15.53714	1739.841	4.056
13213	1452.083	7.475948	0.458929	234.3039	32011.19	5.453294	11.34771	1323.312	3.632
37209	1082.304	6.092504	0.590675	172.7897	33390.79	4.536697	8.592447	1008.474	3.021
19924	1357.431	7.73963	0.460688	230.6641	32546.31	5.612947	11.33333	1228.986	3.695
52628	821.0245	8.164343	0.436721	241.0678	33841.93	5.845084	9.391099	732.8317	3.898
52651	901.1927	6.982489	0.535436	204.9486	37165.06	5.075487	8.635678	826.6177	3.423
24786	1407.246	4.81184	0.675452	143.4869	36012.78	3.645767	9.570631	1315.649	2.628
14956	1754.293	7.132721	0.487237	234.4941	39501.93	5.314043	13.11858	1582.196	3.636
79589	337.312	7.537604	0.500531	209.0296	32715.38	5.600335	6.52381	294.7519	3.520
31268	321.2041	7.614678	0.499127	237.1695	33972.94	5.577512	5.659259	289.1769	3.376
77609	366.3035	7.803757	0.475354	219.2463	32352.5	5.643267	6.865445	319.1692	3.664
77973	352.9346	8.384395	0.44187	246.7287	31692.45	6.045794	6.824669	306.3585	3.751

30622	308.7597	8.352334	0.43692	241.1789	31557.51	6.008109	6.518592	266.2677	3.717
30302	319.0633	8.133997	0.454594	239.3264	32077.05	5.853904	6.384835	278.2972	3.657
32459	295.6701	7.545485	0.5018	215.7871	33416.07	5.425032	5.806839	261.9507	3.433
3248	292.3471	8.115593	0.465521	242.7805	33080.28	5.856086	6.101537	255.1184	3.595
22021	410.5226	10.35771	0.099132	139.3247	4202.643	7.565755	15.07742	183.194	5.317
53343	485.9022	10.35067	0.110644	149.2204	6140.477	7.751996	15.78817	236.6358	5.391
30337	497.1946	10.28478	0.108548	168.4634	7812.696	7.795589	16.42043	227.5641	5.419
12489	594.4043	10.3865	0.108879	196.4151	12990.21	8.101288	18.25591	261.1259	5.533
35111	718.2731	10.01198	0.145587	169.4903	11785.51	7.815271	19.44301	340.2425	5.604
4742	667.5882	9.771778	0.163967	161.8656	8083.054	7.386772	19.19462	299.1546	5.510
20308	656.4247	10.58563	0.074934	175.1989	6649.684	7.872505	19.93871	258.8726	5.658
24837	639.0151	10.55903	0.06523	174.5978	4005.617	7.665219	19.37419	263.6557	5.637
54106	654.8204	10.60915	0.062966	172.3237	4671.228	7.726138	19.52366	273.6473	5.651
77741	532.1613	10.56991	0.057101	178.1355	4256.509	7.699814	17.95054	209.9395	5.515

)5624	360.2086	10.45802	0.066933	176.1419	3346.094	7.484904	14.77634	141.8683	5.253
78298	384.3968	10.46498	0.071064	165.7108	3083.289	7.434897	14.77742	166.0247	5.281
78298	384.3968	10.46498	0.071064	165.7108	3083.289	7.434897	14.77742	166.0247	5.281
78298	384.3968	10.46498	0.071064	165.7108	3083.289	7.434897	14.77742	166.0247	5.281
78298	384.3968	10.46498	0.071064	165.7108	3083.289	7.434897	14.77742	166.0247	5.281
78298	384.3968	10.46498	0.071064	165.7108	3083.289	7.434897	14.77742	166.0247	5.281
)8974	1017.651	10.69438	0.049168	207.7624	9636.927	8.05972	24.55376	414.7632	5.951
)6436	1050.576	10.72826	0.040902	216.8753	9804.481	8.111188	25.15484	417.8104	5.980
57799	712.1763	10.65244	0.060155	197.2559	9304.268	7.897405	20.28387	300.7409	5.710
)1901	464.6409	10.43608	0.079247	183.5161	9008.243	7.629753	15.3957	227.6133	5.317
96937	495.3366	10.36784	0.084055	185.7667	9116.951	7.581601	15.3086	260.9833	5.286
70478	738.7333	10.54002	0.060884	200.6882	10668.34	7.829715	19.13548	372.5666	5.565
41744	751.8333	10.60241	0.067502	198.743	8749.677	7.858999	19.61398	367.1252	5.635
55305	590.0172	10.54059	0.062636	199.1656	7565.304	7.808546	17.36559	288.4534	5.477
4583	543.1215	10.48455	0.073173	194.2613	6502.64	7.685609	16.43333	273.0671	5.409

53046	375.2817	10.41605	0.085319	180.4	4732.184	7.41739	13.48817	193.3509	5.113
35174	315.1161	10.30867	0.102261	171.5054	3508.497	7.248509	11.88387	173.8897	4.939
19567	297.5376	10.13857	0.103862	167.3183	3000.501	6.963356	11.64516	161.9279	4.914
21768	311.1925	10.21825	0.109311	172.5839	3180.809	7.206315	11.78387	172.3329	4.941
53183	349.5763	10.33808	0.087784	170.8108	4412.506	7.339166	13.11613	177.5435	5.108
53279	418.6108	10.34256	0.081528	178.1204	5287.598	7.410746	13.87957	225.9683	5.158
39943	560.5742	10.40012	0.076722	176.5871	6444.113	7.514077	15.7914	311.2059	5.278
28186	801.2452	10.55201	0.064552	182.4022	8525.643	7.786143	19.77204	410.3115	5.641
07815	828.2452	10.52166	0.08293	169.7591	7791.009	7.680083	19.87742	433.1334	5.632
12372	185.2097	10.3146	0.094021	135.7323	1789.013	7.182871	10.32581	78.5874	4.770
28001	183.2731	9.956346	0.120735	149.7505	1164.329	6.761723	9.292473	96.92306	4.621
18308	122.4344	9.815311	0.157088	140.9505	2875.019	7.028025	8.094624	56.91148	4.485
36724	72.38925	9.890728	0.162114	144.6387	2215.672	7.12184	6.402151	31.40172	4.133
33019	59.53118	9.860148	0.152871	150.0753	958.261	6.800228	6.027957	23.19492	4.019
53662	306.4409	10.55835	0.074183	225.8043	3881.684	7.652071	13.46237	125.2056	5.139
9665	476.8108	10.5976	0.059422	230.2043	4212.752	7.689055	16.55269	202.8193	5.400

30683	609.8946	10.61077	0.068065	236.1677	3919.299	7.712939	19.02151	248.077	5.590
2767	566.4731	10.62475	0.055833	256.2194	3593.72	7.678844	18.4043	227.7548	5.563
677	319.0065	10.603	0.073504	249.6903	4503.474	7.820118	13.7957	128.6851	5.178
04728	167.3753	10.32603	0.09446	207.857	3346.258	7.408357	9.988172	67.61169	4.702
01518	194.3624	10.25544	0.110622	184.4914	3752.783	7.365976	10.15806	91.17609	4.768
33758	279.5677	10.47288	0.084697	203.1871	4530.546	7.673612	12.40215	125.7544	5.039
25583	456.1548	10.57285	0.071244	231.1656	4774.465	7.807924	16.07527	197.7406	5.377
28579	314.0419	10.41014	0.08675	199.9151	3349.944	7.470649	13.16667	140.6808	5.128
12234	374.6097	10.38706	0.093736	206.6978	3615.568	7.494355	14.00968	178.3386	5.231
01802	339.1538	10.28379	0.105278	223.1925	3083.211	7.374423	12.82473	174.68	5.101
11114	285.7946	10.08651	0.119338	233.8032	2740.311	7.168942	11.23118	159.6552	4.889
37784	189.9473	9.888233	0.130073	242.2398	2151.963	6.831626	9.151613	106.1953	4.603
25249	205.5753	9.758487	0.148868	236.9645	2147.208	6.879137	9.06129	123.4683	4.575
13472	263.8032	10.08164	0.128474	230.8914	2564.768	7.078104	10.63978	150.5982	4.814
28198	225.171	9.966457	0.13923	219.0828	2396.106	7.064616	9.837634	128.3919	4.701

35786	186.2591	10.00981	0.132406	216.0398	3075.32	7.123131	9.37957	98.28281	4.663
35505	336.6656	10.36566	0.097839	224.0484	5544.212	7.678655	13.18172	162.9078	5.117
52424	378.9075	10.4304	0.085054	212.8323	4756.172	7.633813	13.52473	195.9892	5.108
43198	476.2161	10.4188	0.088703	203.2183	5597.902	7.65611	14.83978	255.9969	5.238
38116	522.9774	10.35331	0.063217	280.5731	4413.462	7.230901	16.46559	251.8617	5.424
54775	701.2452	10.62877	0.046637	263.5634	5017.958	7.830312	20.62796	275.7326	5.707
08739	543.0011	10.56952	0.056054	270.5172	3185.624	7.560913	17.91505	222.0519	5.527
37445	409.9269	10.50213	0.065391	294.529	1851.393	7.226007	15.89892	157.1511	5.349
59467	250.1699	10.33481	0.081694	290.7183	1219.116	7.007429	12.35914	97.42156	5.005
23892	521.2333	10.5887	0.054111	288.3	2250.49	7.390991	18.09785	193.7012	5.506
74367	284.1194	10.46904	0.074212	274.7473	2234.301	7.344578	13.32366	106.5995	5.093
10574	531.1828	10.54597	0.051219	256.7204	2196.849	7.356681	18.68602	182.0154	5.541
30725	546.8032	10.60083	0.053317	260.5409	3514.493	7.562258	18.15806	217.0879	5.537
33668	774.0624	10.65405	0.055961	261.8301	8533.375	8.113528	21.49677	311.9511	5.781

03772	702.8473	10.49445	0.083036	274.6817	13905.1	8.206858	20.17419	295.8492	5.709
34186	374.6118	9.732161	0.187947	126.9538	11009.28	7.621822	13.76237	185.2091	5.107
36639	562.2516	10.45058	0.101057	174.5656	9357.373	7.962906	17.51183	255.5875	5.503
00719	671.343	10.60754	0.065512	181.8978	6066.313	7.964765	18.92581	313.1569	5.607
57491	637.4011	10.58762	0.060127	196.9602	4619.313	7.805948	18.49785	295.2306	5.560
31566	526.6043	10.54917	0.060097	187.1548	4295.03	7.704125	16.65161	249.3281	5.417
5032	511.8269	10.61444	0.056551	215.4742	3588.028	7.664256	17.76237	196.3253	5.499
43166	451.0591	10.50024	0.071467	205.6355	3061.391	7.549547	15.93226	197.2223	5.387
7325	397.1172	10.47997	0.080706	212.2763	3105.57	7.539098	14.83333	177.0894	5.284
0054	404.2172	10.54757	0.066358	218.2817	3648.903	7.637486	15.76344	155.7311	5.335
36876	443.8194	10.6097	0.072405	221.8473	3721.082	7.703281	16.3871	175.2824	5.410
68265	202.0075	10.40424	0.093873	187.1194	2864.862	7.461317	10.74731	86.50282	4.829
0393	134.6731	10.22578	0.120306	168.5849	2668.963	7.258707	8.922581	55.06067	4.568
16875	122.7118	10.09424	0.11905	179.286	2829.755	7.284202	8.311828	53.62534	4.471
05609	157.5516	10.32871	0.11247	192.2269	3180.722	7.353511	9.370968	69.73658	4.632
76721	244.1269	10.41245	0.097619	197.914	3716.442	7.548491	11.24946	117.5765	4.888

31833	377.6054	10.52039	0.080286	183.6763	6013.419	7.817811	14.56022	165.6055	5.279
97199	481.6462	10.60028	0.068841	158.3645	8888.842	8.053644	16.73871	201.4618	5.439
98501	377.8194	10.45568	0.071989	125.228	7066.991	7.876846	14.56989	165.5376	5.256
31797	685.4376	10.66616	0.052988	190.9215	5597.126	7.915721	19.63548	299.8854	5.661
53729	482.928	10.59517	0.060537	177.0484	3439.003	7.643871	16.79677	200.7963	5.435
25344	568.7978	10.64169	0.064917	193.5699	5944.561	7.836624	18.04731	243.0924	5.520
73028	179.0075	10.245	0.096025	166.5946	2640.624	7.275544	10.14731	76.03959	4.726
00251	505.0398	10.63335	0.052743	211.7086	4551.703	7.787232	17.75161	189.92	5.493
84352	454.0312	10.60673	0.064422	191.3817	3756.815	7.662957	16.23548	190.4402	5.380
14659	407.8495	10.55053	0.066557	194.471	3993.232	7.653411	15.48817	167.966	5.304
29183	351.5753	10.55376	0.065812	182.3065	3764.823	7.600527	14.63548	137.3779	5.199
61019	208.5613	10.28507	0.091178	167.8774	2792.74	7.309385	10.8043	91.82837	4.815
71369	143.2065	9.952188	0.126686	157.7032	2083.411	6.987318	8.477419	71.33981	4.513
16347	305.3634	10.31705	0.096253	167.6387	3020.067	7.370501	12.21505	156.1559	5.003

7415	485.9559	10.37104	0.118838	126.2269	2496.743	7.382252	15.56452	243.7018	5.370
70213	881.329	10.51099	0.089948	141.3828	3219.903	7.520176	21.13763	434.5294	5.702
67115	758.1129	10.42241	0.08859	137.7151	2744.492	7.382127	18.33441	421.9624	5.444
77974	541.1978	10.13949	0.108268	137.7957	2023.56	7.105363	14.87097	320.0522	5.196
00301	614.4731	10.19765	0.096547	136.7419	1844.899	6.962651	16.24301	350.6377	5.316
39777	443.4817	10.03139	0.124536	134.9398	1483.764	6.979785	13.7828	253.5163	5.101
53411	386.9151	10.0819	0.116921	121.5925	1845.79	7.076692	13.74946	197.8673	5.171
58916	604.829	10.4724	0.074591	130.3043	4412.745	7.508843	17.14301	310.9462	5.477

Correlation Coeffeciant between the features of images:

Correlation quantifies the extent to which two quantitative variables, X and Y, “go together.” When high values of X are associated with high values of Y, a positive correlation exists. When high values of X are associated with low values of Y, a negative correlation exists. If the correlation is 0 that mean no correlation between them. The correlation coefficients of Haralick’s Features show in the table bellow.

Table(A2) show correlation coeffeciant between the features:

orrelation	inertia	entropy	inverse_ diff	sum_ avg	sum_ var	sum_ entropy	diff_ avg	diff_ var	diff ent

.610095	0.436981	-0.96366	0.926435	-0.16405	0.742716	-0.95975	-0.52619	0.569901	-0.8
	0.125179	-0.67884	0.770391	0.248157	0.751649	-0.66422	-0.67751	0.282649	-0.7
.125179	1	-0.52889	0.481483	0.398884	0.624104	-0.46011	0.227303	0.970758	-0.3
0.67884	-0.52889	1	-0.98023	0.003434	-0.84081	0.986653	0.570253	-0.67605	0.9
.770391	0.481483	-0.98023	1	0.107882	0.897153	-0.97368	-0.63388	0.641477	-0.9
.248157	0.398884	0.003434	0.107882	1	0.492074	0.027769	0.076908	0.380955	-0.0
.751649	0.624104	-0.84081	0.897153	0.492074	1	-0.81788	-0.44559	0.740168	-0.8
0.66422	-0.46011	0.986653	-0.97368	0.027769	-0.81788	1	0.652749	-0.6268	0.9
0.67751	0.227303	0.570253	-0.63388	0.076908	-0.44559	0.652749	1	-0.00869	0.7
.282649	0.970758	-0.67605	0.641477	0.380955	0.740168	-0.6268	-0.00869	1	-0.5
0.7436	-0.36244	0.948271	-0.9594	-0.03135	-0.81114	0.972079	0.781717	-0.55599	1
.069987	-0.14464	-0.08246	0.150506	0.041343	0.096375	-0.23036	-0.53943	-0.00911	-0.3
0.38539	-0.35617	0.773006	-0.71969	0.21307	-0.53747	0.815344	0.470552	-0.47302	0.7