

Chapter one

Introduction

:1.1Brain anatomy

The human brain which functions as the center for the control of all the parts of human body is a highly specialized organ that allows a human being to adapt and endure varying environmental conditions. The human brain enables a human to articulate words, execute actions, and share thoughts and feelings. In this section the tissue structure and anatomical parts of the brain are described to understand the purpose of this study. The brain is composed of two tissue types, namely gray matter (GM) and white matter (WM). Gray matter is made of neuronal and glial cells, also known as neuroglia or glia that controls brain activity and the basal nuclei which are the gray matter nuclei located deep within the white matter. The basal nuclei include: caudate nucleus, putamen, pallidum and claustrum. White matter fibers consist of many myelinated axons which connect the cerebral cortex with other brain regions. The left and the right hemispheres of the brain are connected by corpus callosum which is a thick band of white matter

.(fibers(Charles.et.al2005

The brain also contains cerebrospinal fluid (CSF) which consists of glucose, salts, enzymes, and white blood cells. This fluid circulates through channels (ventricles) around the brain and the spinal cord to protect them from injury. There is also another tissue called meninges which are the membranes covering the brain and spinal

.(cord(Charles et.al2005

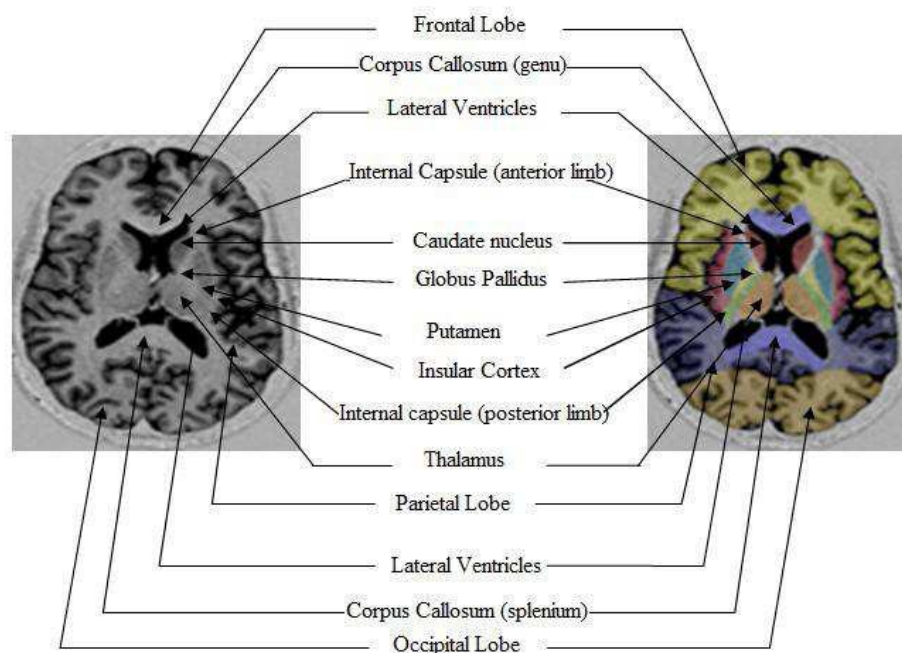


Figure 1-1: Overview Structure of Human Brain, Left Side: An Axial Slice MR Image, Right Side, the ColorCoded Version of Image Left Side

Figure 1-2 shows the anatomy of the brain. It is composed of the cerebrum and the brain stem. The cerebrum is connected with the conscious thoughts, movement and sensations. It further consists of two halves, the right and the left hemispheres. Each hemisphere controls the opposite side of the body. Moreover, each hemisphere is divided into four lobes: the frontal, temporal, parietal and occipital lobes. The cerebellum is the second largest structure of the brain; it is connected

with controlling motor functions of body such as walking, balance, posture and the general motor coordination. It is situated toward the back side of the brain and is linked to brain stems. Both, cerebellum and cerebrum have a very thin outer cortex of gray matter, internal white matter and small but deeply situated masses of the gray matter. The spinal cord is connected to the brainstem. It is located toward the bottom of the brain. Brainstem controls vital functions in human body such as motor, sensory pathways, cardiac, repository and reflexes. It has three structures: the midbrain, pons and medulla .(oblongata (Charles.et.al2005

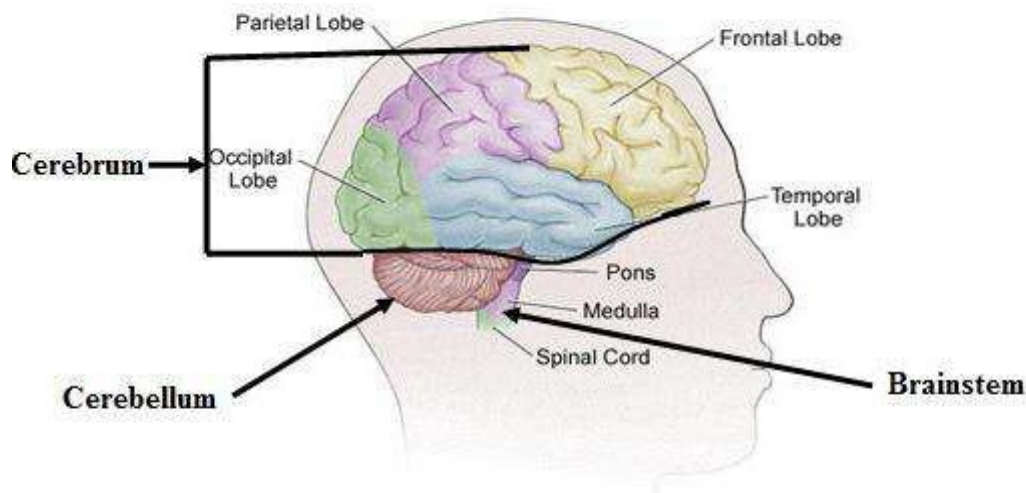


Figure 1-2: The Major Subdivision of Human Brain

:Brain Tumors 1.2

Under certain conditions, brain cells grow and multiply uncontrollably because for some reasons, the mechanism that control normal cells is unable to regulate the growth of the brain cells. The abnormal mass of brain tissue is the brain tumor that occupies space in the skull and interrupts the normal functions of brain and creates an increasing pressure in the brain. Due to increased pressure on the brain, some brain tissues are shifted,

pushed against the skull or are responsible for the damage of the nerves of the other healthy brain tissues (Louis D.N.et.al2007)

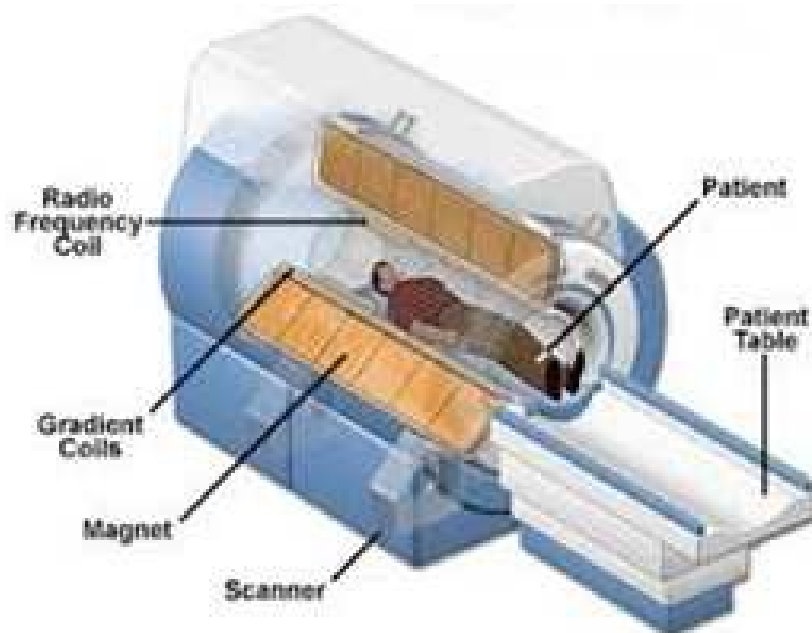
Scientists have classified brain tumor according to the location of the tumor, type of tissue involved, whether they are noncancerous or cancerous. The site of the origin (primary or secondary) and other factors involved (Buckner, et al.2007) World Health Organization (WHO) classified brain tumor into 120 types. This classification is done on the basis of the cell origin and the behavior of the cell from less aggressive to more aggressive behavior. Even, some tumor types are graded ranging from grade I (less malignant) to grade IV (more malignant). This signifies the rate of the growth despite of variations in grading systems which depends on the type of the tumor (Louis D.N.et.al2007) or Primary brain tumors are the tumors that originated in the brain and are named for the cell types from which they originated. They can be benign (non-cancerous) and malignant (cancerous). Benign tumors grow slowly and do not spread elsewhere or invade the surrounding tissues. However, occupying a short space, even the less aggressive tumor can exercise much pressure on the brain and makes it dysfunctional. Conversely, more aggressive tumors can grow more quickly and spread to other tissues. Each of these tumors has unique clinical, radiographic and biological characteristics (Louis.et.al2007) Secondary brain tumors originate from another part of the body. These tumors consist of cancer cells somewhere else in the body that have metastasized or spread to the brain. The most common cause of secondary brain tumors are: lung cancer, breast cancer, melanoma, bladder cancer, certain (sarcomas, and testicular and germ cell tumors (Louis.et.al2007)

MRI Brain Imaging and Characteristics of Brain 1.3

:Tumors

There are a variety of imaging techniques used to study brain tumors, such as: magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), and single photon emission computer tomography (SPECT) imaging and cerebral angiography. In recent years, CT and MR imaging are the most widely used techniques, because of their widespread availability and their ability to produce high resolution images of normal anatomic structures and pathological tissues. Magnetic resonance imaging (MRI) is a method used to visualize pathological or other physiological alterations of living tissues and is commonly used for brain tumor imaging because of the following reasons (Medical Imaging in Cancer Care 2012). It does not use ionizing radiation like CT, SPECT and PET. Its contrast resolution is higher than other techniques mentioned above. Ability of MRI devices to generate 3D space images enables them to have superior tumor localization. Its ability in acquisition of both functional and anatomical information about the tumor during the same scan. Before discussing the MR image characteristics of brain tumors, it is important to describe the working principle of MR imaging. During MR imaging, the patient is placed in a strong magnetic field which causes the protons in the water molecule of the body to align in either a parallel (low energy) or anti-parallel (high energy) orientation with the magnetic field. Then a radiofrequency pulse is introduced which forces the spinning protons to move out of equilibrium state. When a radio frequency pulse is stopped, the protons return to equilibrium state and produce a sinusoidal signal at a frequency dependent on the local magnetic field. Finally, a radio frequency coils or resonators within the scanner

detects the signal and creates the image



(A. O Rodriguez2004)

Figure 1-3: MRI Scanner Cut

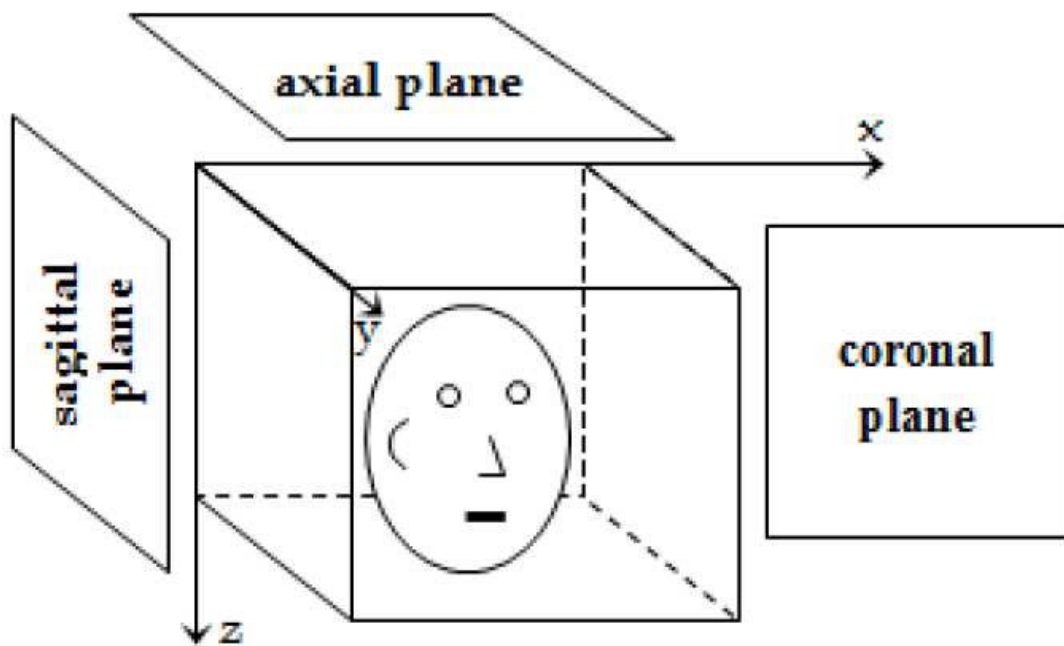
,away(www.teamrads.com/Cases/Neuroanatomy/MRI)

Magnetic-resonance imaging (MRI) is an imaging technique used primarily in medical settings to produce high quality images of the inside of the human body. A MRI is similar to CT, but it does not use X-rays. Instead, a strong, magnetic field is used to affect the orientation of protons, which behave like miniature magnets and tend to align themselves with the external field

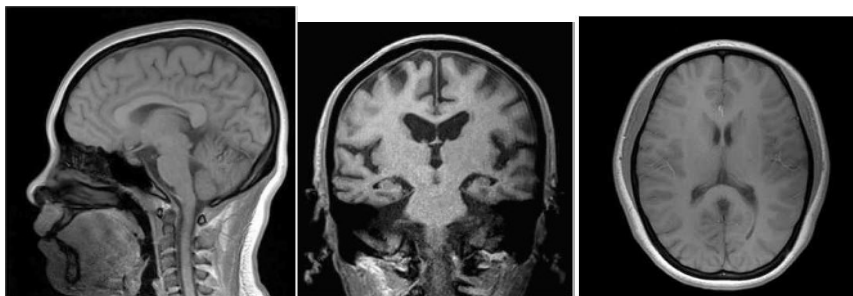
:(MR imaging (MRI 1.4

Raymond V. Damadian invented MRI in 1969 and was the first person to use MRI to investigate the human body (Damadian, 1977). Eventually, MRI became the most preferred imaging technique in radiology because MRI enabled internal structures to be visualized in some detail. With MRI, good contrast between different soft tissues of the body can be observed. This makes MRI suitable for providing better quality images for the brain, the muscles, the heart and cancerous tissues compared with other medical imaging techniques, such as computed tomography (CT) or X-rays [10]. In MRI signal processing considers signal emissions. These are characterized by various magnetic signals weighting with particular values of the echo time (T_g) and the repetition time (T_r). The signal processing has three different images that can be achieved from the same body: T1-weighted, T2 weighted and PD-weighted (proton density). Figure 4 (a) shows that a patient's head is examined from three plans in a clinical diagnosis which are axial plane, sagittal plane and coronal plane. Furthermore, T1-weighted brain MR images from

.(various planes are shown in figure 4 (b), (c), and (d



(a)



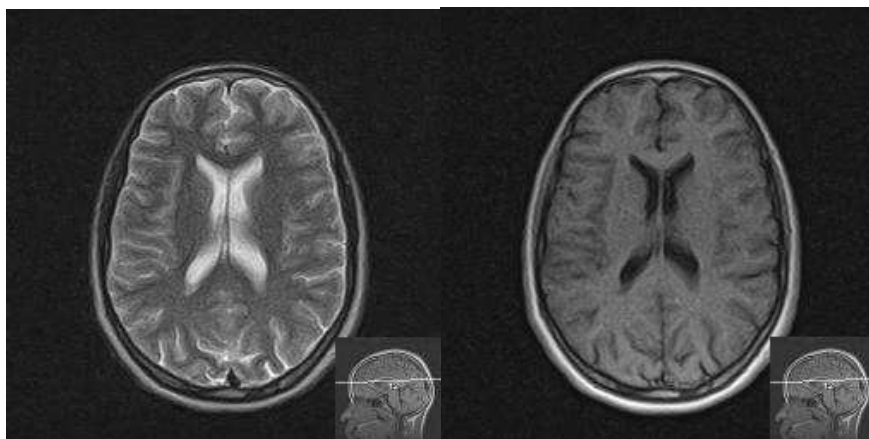
(b)

(c)

(d)

Figure 1-4: Brain MR Images From (b) Axial Plane, (c) Sagittal Plane And (d) Coronal Plane

There are two main MR imaging sequence families, depending on the type of echo recorded: Spin echo sequence and gradient echo sequences. Spin echo (SE) sequence with its variant fast spin echo (FSE) sequence has been the standard MRI pulse sequences for anatomical and pathological details (Li et al 2003). Brain images in MRI scan can be normal or abnormal. The normal brain is characterized by having gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF) tissues. The abnormal brain usually contains active tumor, necrosis and edema in addition to normal brain tissues. Necrosis is a dead cell located inside an active tumor, while edema is located near active tumor borders. Edema, which results from local disruption of blood brain barrier, often overlap with normal tissues and it is always difficult to distinguish from the other tissues [2]. An image from MRI scan is composed of gray level intensity values in the pixel spaces. The gray level intensity values depend on the cell concentration in the volume scanned. A darker region indicates the presence of some abnormality. In normal brain MR images, image intensity level for brain tissues is of the order of increasing brightness from CSF, GM to WM in T1-weighted (T1-w) and from WM, GM to CSF in T2-weighted (T2-w) image. This is illustrated in Figure 5. Sagittal Plane And (d) Coronal Plane



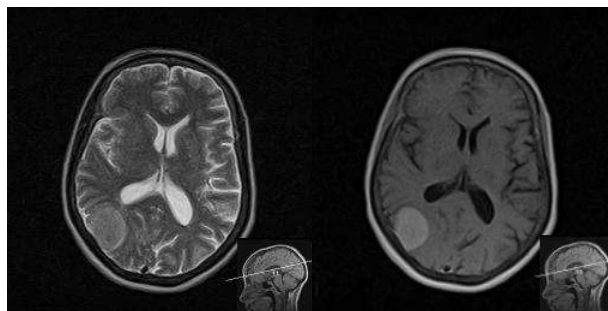
(b)

(a)

Figure 1-5: Original Raw MRI Data from Pioneer Diagnostic Center.

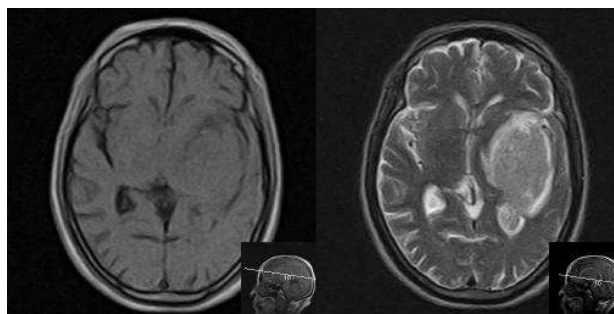
.(a) T1-w axial scan image, (b) T2-w axial scan image

In tumorous brain, MR images intensity level of tumorous tissues exhibit different intensity level on T1-w and T2-w images based on the type of tumor. On T1-w, most tumors have low or intermediate signal intensity but for some tumors this does not hold true, for example, glioblastoma multiforme tumor has high signal intensity. On T2-w most tumors have bright intensity but there are tumors which have low intensity, the classic examples are lymphoma tumors. Figure 6 shows some examples of tumors intensity level characteristics in MRI.



(b)

(a)



(c)

(d)

Figure 1-6 Tumor Region Intensity Characteristics, Original Raw MRI Data from Pioneer Diagnostic Center. (a) And (c) T2-w images, (b) and (d) T1-w Images. Tumor Region in a) Low Intensity, b) High Intensity, c) High Intensity and d) Low Intensity

:1-5 Problem of the research

Brain MRI images were evaluated and diagnosed by the radiologist through visual perception where they use agreed upon defects, therefore the evaluation is subjective rather than objective one. An objective method using image processing (classification) will help in the objectivity of the diagnostic

1-6 Objective of the study

The general objective of this study was to characterize brain tumor in MRI images using image processing in order to give the radiologist an objective second opinion

1-7 Specific Objectives

To classify brain tissue into gray matter, white matter, and tumor •

To segment region of interest 'brain' from image background •

To find the overall classification accuracy and hence the •
.discriminate power of the textural features

Significance of the research 1.8

This study will help in distinguishing tumors in the brain MRI by delimitating and demarcating the outlines of the tumor from the image background and hence it facilitate an automatic method of tracing the tumor outlines through the slices in order to find the size .and volume of the tumor

1.9overview of the study

This study consisted of five chapters with chapter one is an introduction which includeoverview of the brain anatomy, MRI, problem of the study, objectives and overview. Chapter two include literature review while chapter three include material and method used for data collection and analysis. Chapter four presents the result of the study in a line graphs and table and finally chapter five which include the discussion, conclusion, recommendation and references.

Chapter two

Literature review

Texture Analysis 2.1

Texture is an important characteristic of images and refers to the appearance of the image. Image texture is a function of the spatial variation of pixel intensities in an image(Connors et.al 1980) (Kjer et.al 1995) Image texture analysis can provide quantitative information in the form of texture features that is not visible to human vision(Heraldic et.al 1973)Texture features are mathematical parameters computed from the distribution of pixels, which characterize the texture type in the image. The most common method of computing the image texture is to use a statistical based method that analyzes the properties of individual pixel intensities and their spatial distribution within the image(Haralick1979). Statistical based texture analyses are commonly classified as first-order and secondorder textures, based on the number of pixels defining the local features. First-order textures estimate properties of individual pixel values, ignoring the spatial interaction between the neighboring image pixels, whereas second-order textures estimate properties of two or more pixel values occurring at specific .locations relative to each other

First-Order Textures 2.1.1

Textures based on first order statistics are features that can be computed from the gray level histogram. The histogram of an image is the count of the number of pixels in the image that possess a given grey-level value. Figure 2.1shows an example gray-level histogram. The most common first-order texture features are the

.mean, standard deviation, skewness and kurtosis

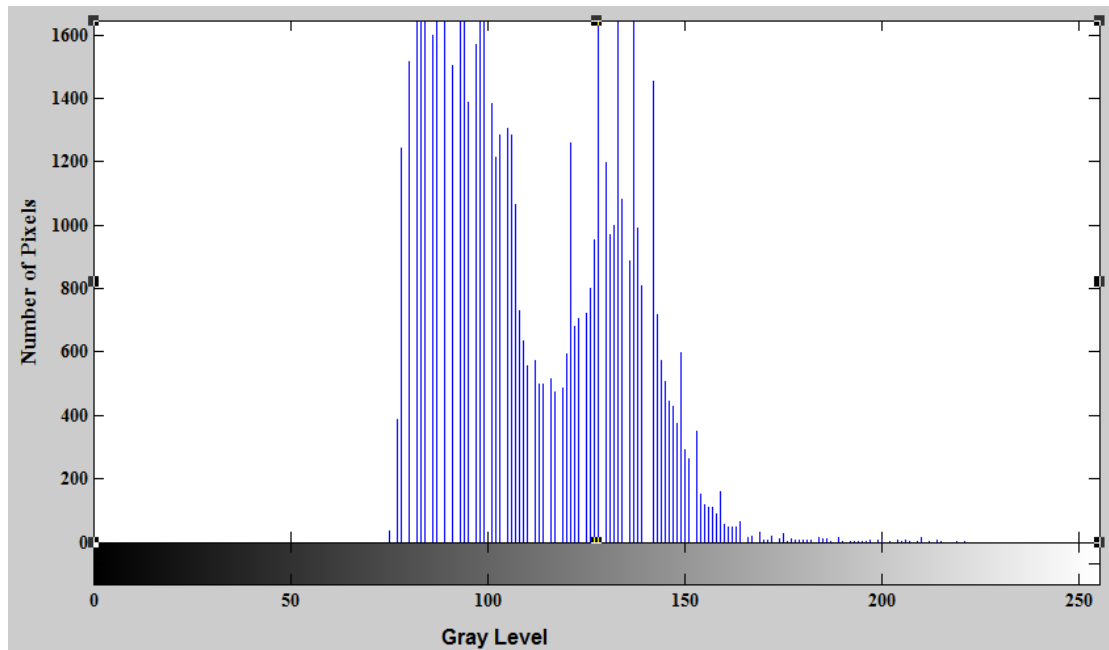


Figure 2-1 Gray-level histogram

Mean of the histogram is the mean of the gray-levels in an image.

((equation 1

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$

Ø1

x = gray levels

n = number of gray-levels

Standard deviation is a measure of how far from the mean the gray values in the

(Images are distributed..(equation 2

$$s = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2}$$

(2

Skewness of the histogram refers to the asymmetry of the distribution of the grayvalues. A distribution is symmetric if the right side of the distribution is similar to the left side of the distribution. If the distribution is symmetric, then the skewness value is zero. A distribution with an asymmetric tail extending out to the right is referred to as positively skewed, while a distribution with an asymmetric tail extending out to the left is referred to as negatively skewed. The skewness of a distribution is defined as:.(equation3

$$sk = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^3}{\left[\sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} \right]^3}$$

3

Kurtosis is a measure of how flat or peaked the top of a symmetric distribution is when compared to a normal distribution. If the grey level distribution is similar to the normal distribution, the kurtosis value is 3. Flat-topped distributions are referred to as platykurtic and have a kurtosis value

of less than 3, while less flat-topped distributions are referred to as leptokurtic and have a kurtosis value greater than 3. The kurtosis of (a distribution is defined as: (equation 4

$$k = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^4}{\left[\sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} \right]^4}$$

(4

The limitation of the histogram-based measurements is that they carry no information regarding the relative spatial position of pixels with one another. The spatial relationship of the pixels can be incorporated by taking in to account the distribution of intensities as well as the position of pixels with equal or nearly equal intensity values. This can be achieved by constructing a gray level co-occurrence matrix as explained in the next section

Second-Order Textures 2.1.2

Textures based on second-order statistics are features that can be computed from the gray level co-occurrence matrix (GLCM). The GLCM is a two-dimensional histogram of gray levels for a pair of pixels separated by a fixed distance (d) at a fixed angle (θ). (Heraldic 1979), It is an estimate of the joint probability $G(i, j)$ of the intensity values of two pixels (i and j), at a certain pixel distance apart along a given direction (i.e., the probability that i and j have the same intensity). This joint probability takes the form of a square matrix with row and column dimensions equal to the number of discrete gray levels (intensities) in the image. If an intensity image contained no texture (intensity variations) the resulting GLCM would be completely diagonal. As the image texture increases (i.e. as the local pixel intensity variations increase), the off-diagonal

values in the GLCM become larger. GLCMs are usually computed with neighboring pixels defined in angular directions 0° , 45° , 90° and 135° . Figure 2.2 shows an example to construct a GLCM. Consider a 4x4 image (Figure 2.2a) with 4 gray-levels from 0 to 3 (Figure 2.2b). A generalized GLCM is shown in Figure 1.17c where (i, j) stands for the number of times gray-level i and j satisfy the condition stated by the offset distance vector d and angle θ . The resulting four GLCMs for $d = [0 \ 1]$ and $[0 \ -1]$ and $\theta = 0^\circ, 45^\circ, 90^\circ, 135^\circ$ are shown in Figure 2.2d



Figure 1.17a Sample image.

0	0	1	1
0	0	1	1
0	2	2	2
2	2	3	3

Figure 1.17b Gray-levels in the sample image.

figure2.2b Gray-levels in the sample image Figure 2-2a sample image

(i, j)	0	1	2	3
0	(0,0)	(0, 1)	(0, 2)	(0, 3)
1	(1,0)	(1, 1)	(1, 2)	(1, 3)
2	(2,0)	(2, 1)	(2, 2)	(2, 3)
3	(3,0)	(3, 1)	(3, 2)	(3, 3)

Figure2.2c general form of a GLCM

4	2	1	0	4	1	0	0
2	4	0	0	1	2	2	0
1	0	6	1	0	2	4	1
0	0	1	2	0	0	1	0

Figure2.2dGLCM $\theta = 0^\circ$

figure2.2e GLMC $\theta = 45$

6	0	2	0	2	1	3	0
0	4	2	0	1	2	1	0
2	2	2	2	3	1	0	2
0	0	2	0	0	0	2	0

Figure2.2dGLCM $\theta = 90^\circ$

figure2.2GLCM $\theta = 135^\circ$

GLCMs as seen above are symmetric matrices. Hence either upper or lower triangle is

used for calculation of the second-order features. Each e probability of co-occurrence of the pixel gray-levels. The second-order texture features can then be calculated using the formulas shown below. Each of the five GLCM-based second-order texture features that are

:used in this thesis are described below

Entropy is the measure of randomness of the GLCM. It describes the amount of chaos or disorder within the elements of the GLCM.

(Entropy is higher when the image is nonuniform..(equation5

$$Entropy = -\sum_{i,j} G(i,j) \log_2 G(i,j)$$

(5)

$G(i, j)$ = probability of co- occurrence of the pixel gray-levels

Homogeneity measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. It is also known as inverse difference moment. It is sensitive to the near diagonal elements of the GLCM. It is higher for a diagonal GLCM..(equation6

$$Homogeneity = \sum_{i,j} \frac{1}{1+|i-j|} G(i,j)$$

6

Inertia measures the intensity or gray-level variation between the reference pixel and its neighbor over the whole image. It describes the local variations in the GLCM. It is inversely correlated to homogeneity and will be lower for a diagonal GLCM.(equation7

$$Inertia = \sum_{i,j} (i-j)^2 G(i,j)$$

7

Correlation measures how correlated a reference pixel is to its neighbor over the whole image. It describes the joint probability occurrence of the specified pixel pairs

Correlation is 1 or -1 for a perfectly positively or negatively correlated image.(equation8

$$Correlation = \sum_{i,j} \frac{(i-\mu)(j-\mu)G(i,j)}{\sigma^2}$$

8

μ and σ are the mean and standard deviation.

Energy describes the uniformity of the image. It measures the sum of squared elements of the GLCM. It is also known as angular second moment feature. Energy is .(high if the image is homogenous.(equation9

.

$$Energy = \sum_{i,j} G(i,j)^2$$

)(9

Texture Analysis of Medical Images 2.1.3

MR images hold a large amount of texture information that may be relevant for clinical diagnosis. Due to its inherent resolution limitation, MR images are not capable of providing microscopic tissue information that can be evaluated visually. However, histological changes present in various diseases may generate textural changes in the MR image that can be quantified through .texture analysis

Image texture analysis has been used in a range of MR studies for classifying tissues in brain tumors. It has also been used to differentiate between different tumor grades (Zacharakiet.al2009) and discriminate between benign, malignant, and normal tissue .(types on MR images (Herlidou.e.ta2003

Texture analysis has been used to study the effects of traumatic brain injury on texture features. (Holli et.al2003) Genetic features have been discovered by texture analysis that could favor prognosis in low grade oligodendroglioma(. Brown Ret.al2008) Texture analysis has been used to segment structures in the normal brain, (Saied N.et.al2002)(Alejo et.al2003), as well as in epilepsy to identify

abnormalities in the hippocampus(Yu O.et.al2001) by detecting differences in the texture features. Image texture analysis has been used in a range of CT and MRI studies for classifying non- cerebral tissues. Texture analysis has been used on computed tomography (CT) images to detect micro calcification in breast cancer (KulkarniA,et.al2010) micro calcification susceptibility effects on breast MRI, (James.et.al2001) and to analyze breast tumors on contrast-enhanced MRI(James et.al1997)Texture differences were observed in MR images of the spinal cord between normal subjects and patients with relapsing multiple sclerosis before the atrophy was visually detectable(Mathias,et.al1999) .Texture analysis has also been successfully applied to the classification of pathological tissues in the lungs(Chabot.etal2003) and skeletal (muscles(Herlidou.et.al2003

-.:Previous studies 2.2.1

this study is to present an analytical method to detect lesions or tumors in digitized medical images for 3D visualization. The authors developed a tumor detection method using three parameters; edge (E), gray (G), and contrast (H) values. The method proposed here .studied the EGH parameters in a supervised block of input images These feature blocks were compared with standardized parameters (derived from normal template block) to detect abnormal occurrences, e.g. image block which contain lesions or tumor cells. The abnormal blocks were transformed into three-dimension space for visualization and studies of robustness. Experiments were performed on different brain disease based on single and multiple slices of the MRI dataset. The experiments results have illustrated that our proposed conceptually simple technique is able to effectively detect tumor blocks while being computationally efficient. In this paper, we present a prototype

system to evaluate the performance of the proposed methods, comparing detection accuracy and robustness with 3D visualization .((Phooi 2005

This study to present an automated segmentation method which allows rapid identification of Tumor tissues/pathological structure with an accuracy and reproducibility comparable to those of manual segmentation. The authors uses the wiener filter for the removal of noise and then applies a new marker based watershed segmentation method using image processing and digital processing algorithms to detect Tumor tissues of Brain. This method is simple and intuitive in approach and provides higher computational efficiency along with the exact segmentation of an image. The proposed technique has been implemented on MATLAB 7.3and the .(results are compared with the existing techniques (Rahul 2011

A tumor also known as neoplasm is a growth in the abnormal tissue which can be differentiated from the surrounding tissue by its structure. A tumor may lead to cancer, which is a major leading cause of death and responsible for around 13% of all deaths world-wide. Cancer incidence rate is growing at an alarming rate in the world. Great knowledge and experience on radiology are required for accurate tumor detection in medical imaging. Automation of tumor detection is required because there might be a shortage of skilled radiologists at a time of great need. We propose an automatic brain tumor detection and localization framework that can detect and localize brain tumor in magnetic resonance imaging. The proposed brain tumor detection and localization framework comprises five steps: image acquisition, pre-processing, edge detection, modified histogram clustering and morphological operations. After morphological operations tumors appear as pure white color on pure black backgrounds. We used 50 neuroimages to

optimize our system and 100 out-of-sample neuroimages to test our system. The proposed tumor detection and localization system was found to be able to accurately detect and localize brain tumor in magnetic resonance imaging. The preliminary results demonstrate how a simple machine learning classifier with a set of simple image-based features can result in high classification accuracy. The preliminary results also demonstrate the efficacy and efficiency of our five-step brain tumor detection and localization approach and motivate us to extend this framework to detect and localize a variety of other types of tumors in other types of medical imagery. (.

(Azhari1,et.al 2014

in this study Feature extraction is a method of capturing visual content of an image. The feature extraction is the process to represent raw image in its reduced form to facilitate decision making such as pattern classification. We have tried to address the problem of classification MRI brain images by creating a robust and more accurate classifier which can act as an expert assistant to medical practitioners. The objective of this paper is to present a novel method of feature selection and extraction. This approach combines the Intensity, Texture, shape based features and classifies the tumor as white matter, Gray matter, CSF, abnormal and normal area. The experiment is performed on 140 tumor contained brain

MR

images from the Internet Brain Segmentation Repository. The proposed technique has been carried out over a larger database as compare to any previous work and is more robust and effective. PCA and Linear Discriminant Analysis (LDA) were applied on the training sets. The Support Vector Machine (SVM) classifier served as a comparison of nonlinear techniques Vs linear ones. PCA and LDA methods are used to reduce the number of features used. The feature selection using the proposed technique is more beneficial as it analyses the data according to grouping class variable and gives

reduced feature set with high classification accuracy.(Rathil and (Palani2011

This study about a number of different quantitative models that can be used in a medical diagnostic decision support system. The complexity of the diagnostic task is thought to be one of the prime determinants of model selection. Using histogram equalization the input image is pre-processed and segment the suspicious portion from the image based on markov random field algorithm for segmentation method. Features are extracted based on texture, fractal and histogram features, finally the classification is done by (using the support vector machine approach (K.Vinotha5, May 2014

In this work proposed an implementation of evaluation method known as image mosaicking in evaluating the MRI brain abnormalities segmentation study. 57 mosaic images are formed by cutting various shapes and size of abnormalities and pasting it onto normal brain tissue. PSO, ANFIS, FCM are used to segment the mosaic images formed. Statistical analysis method of receiver operating characteristic (ROC) was (used to calculate the accuracy(-Shafab Ibrahim, Noor Elaiza2011

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Computed Tomography is one of the modalities that can be used to diagnose brain tumor. However this modality only capturing the image without extracting the tumor completely. The process of extracting medical images is the most challenging field nowadays. Most of the technique used is more on MRI modality compared to CT images because it is higher resolutions. This project described two methods the detection and extraction of brain tumor from patient's CT scan images of the brain from two brain tumor patients. Image segmentation used to detect the tumor. The process involves the extraction and segmentation of brain tumor from CT images of a male patient using MATLAB software. The severity of the tumor automatically determined by measuring the volume. Histogram

analysis used to detect the level of the tumor depending on the difference in color intensity for different object density in (the image(. Rania Al-Ashwaletal Elpapageevgious et.al 2008)applied soft computing in their work) proposed a fuzzy cognitive map (FCM) to find the grade value of tumor. Authors used the soft computing method of fuzzy cognitive maps to represent and model expert's knowledge FCMgrading model achieved a diagnostic output accuracy of 90.26% & 93.22 % of brain tumors of low grade and high grade respectively. They proposed the technique only for Characterization and accurate determination of grade Matthew et.al 1998)in this proposed a system that automatically segments and lables). tumor in MRI of the human brain. They proposed a system which integrates knowledgebased techniques with multispectral analysis. The results of the system generally correspondwell to ground truth, both on a per state basis and more importantly in tracking total volumeduring treatment over time

Chapter Three

Materials and Methods

:MRI system 3.1

MRI system used for collecting brain images were those at Alnelain hospital, Philips intera 1.5 Tesla

:Design of the study 3.2

This study is analytic study used normal MRI brain images and MRI images with brain tumors for classification and delineation of tumor boarder

:Population of the study 3.3

The population of this study was data set (brain MR Images), where the brain were free from disease for control cases and the test brain MRI images include patient diagnosed as having brain tumor. The study include both gender with their age ranged from 18 years to 83years old

:Sample size and type 3.4

This study consisted of 50 patients having axial, sagittal and coronal views that include brain tumor and they were selected randomly from a set of 200 patients

:Place and duration of the study 3.5

This study was carried out in the period from January 2015 to June (2015 in Khartoum state at Alhelwan hospital

Methods of data collection *Technique* 3.6

Imaging protocols The brain was imaged using a standard head coil, with section Thickness of 8 mm on all sequences. The MR imaging protocols acquisition of T2-weighted and T1-weighted

:Methods of analysis 3.7

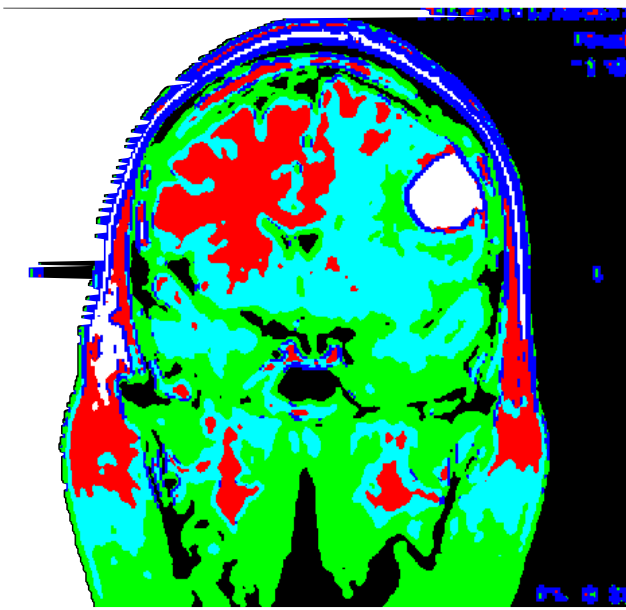
After that MRI images were stored in computer disk were viewed by the Radiant, Ant DICOM in computer to select the axial images that suit the criteria of research population then uploaded into the computer based software Interactive Data Language (IDL) where the DICOM image converted to TIFF format to suit IDL platform. Then the image were read by IDL in TIFF format and the user clicks on areas represents the background, grey matter, white matter, CSF and tumor in case of test group; in these areas a window 3×3 pixel were generated and textural feature for the classes center were generated. These textural features include coefficient of variation, standard deviation, variance, signal, energy, and entropy. These features were assigned as classification centre used by the Euclidian distances to classify the whole image. The algorithm scans the whole image using a window; 3×3 pixels and computes the above mentioned textural features and then computes the distance (the

Euclidean distance) between the calculated features during the scanning and the class's centers and assigns the window to the class with the lowest distance. Then the window interlaced one pixel and the same processes started over again till the entire image were classified and classification maps were generated. After all images were classified the data concerning the brain tissues (CSF, grey, and white matter) and tumour entered into SPSS with its classes to generate a classification score using stepwise linear discriminate analysis; to select the most discriminate features that can be used in the classification of brain tissues in MRI images. Where scatter plot using discriminate function were generated as well as classification accuracy and linear discriminate function equations to classify the brain tissues into the previous classes without segmentation process for unseen images in routine work. The delineation of brain tumor done by further processing of the classification using region label function to segment the brain tumor from the other classes and convert the segmented brain tumor from classification map with pseudo-color to binary image to extract (segment) the brain tumor from the whole original image. Then by applying Sobel function the outline of the binary image was generated and the spatial location of the pixels was used to delineate the brain tumor on the original image using read line

Ethical approval 3.8

The ethical approval was granted from the hospital and the radiology department; which include commitment of no disclose any .information concerning the patient identification

Chapter four Results



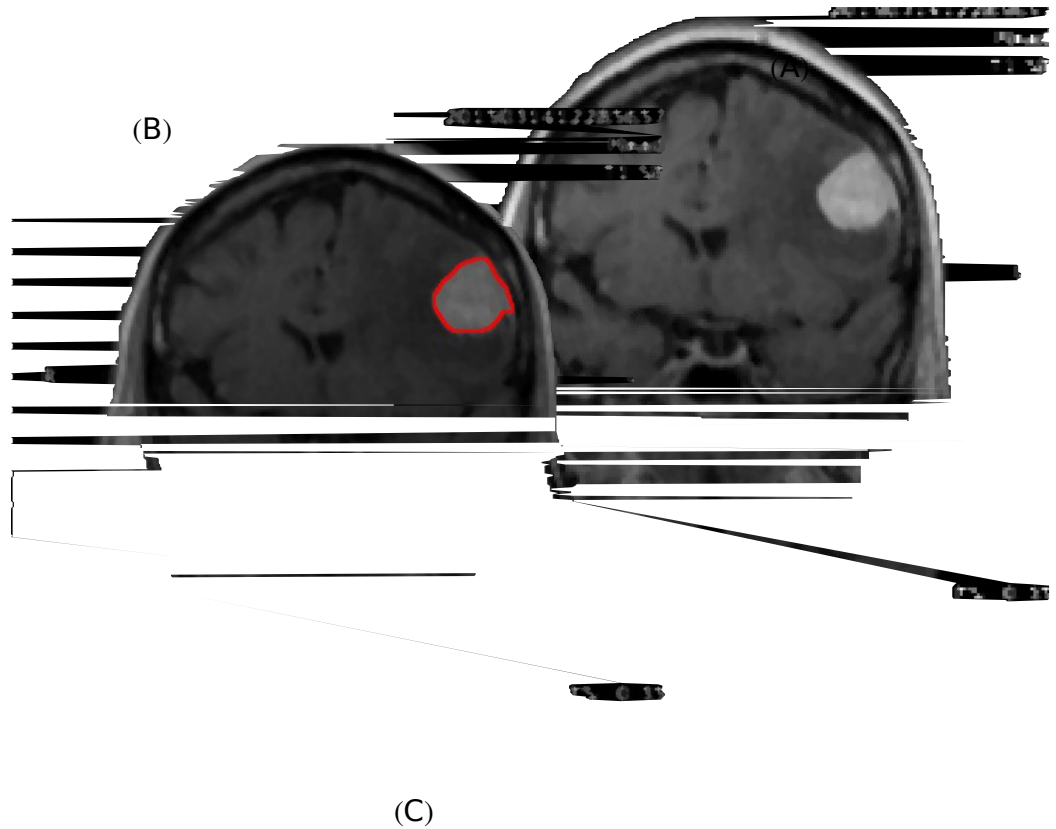


Figure 4-1 (A)an original axial MRI image (B) classification map of the original image using .Euclidian distance, (C) an original image with tumor region delineated

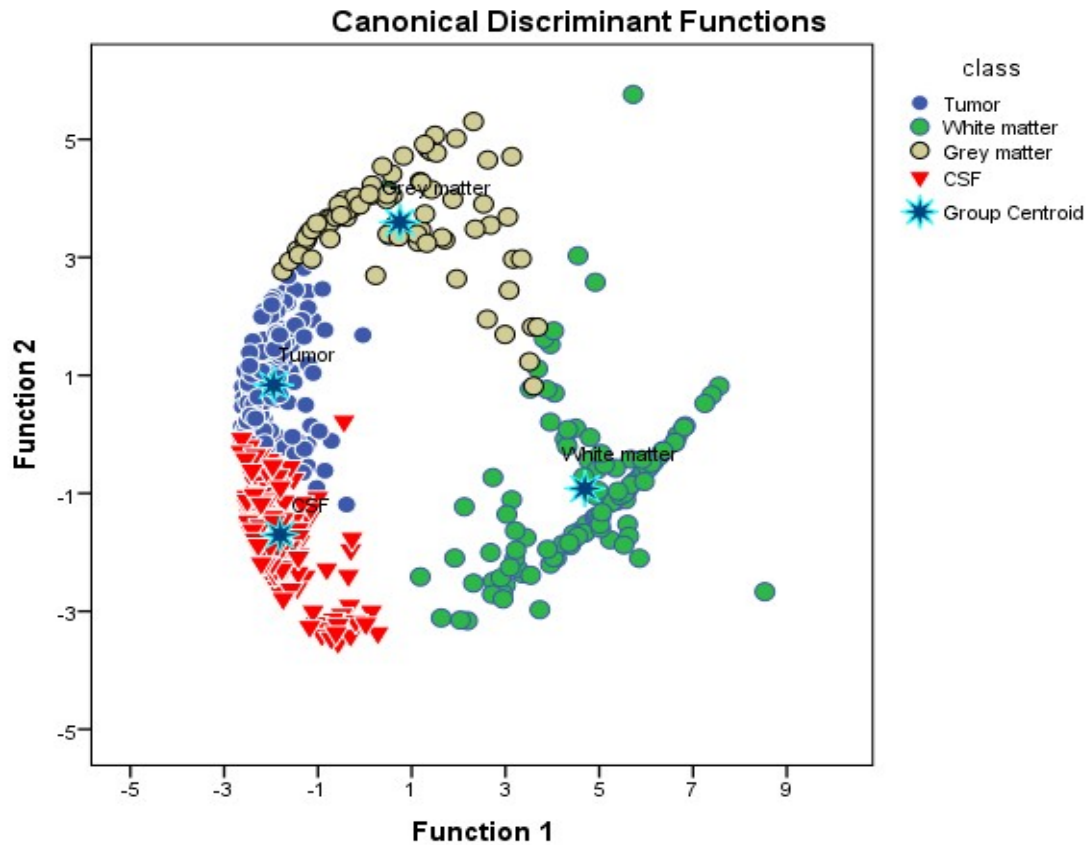
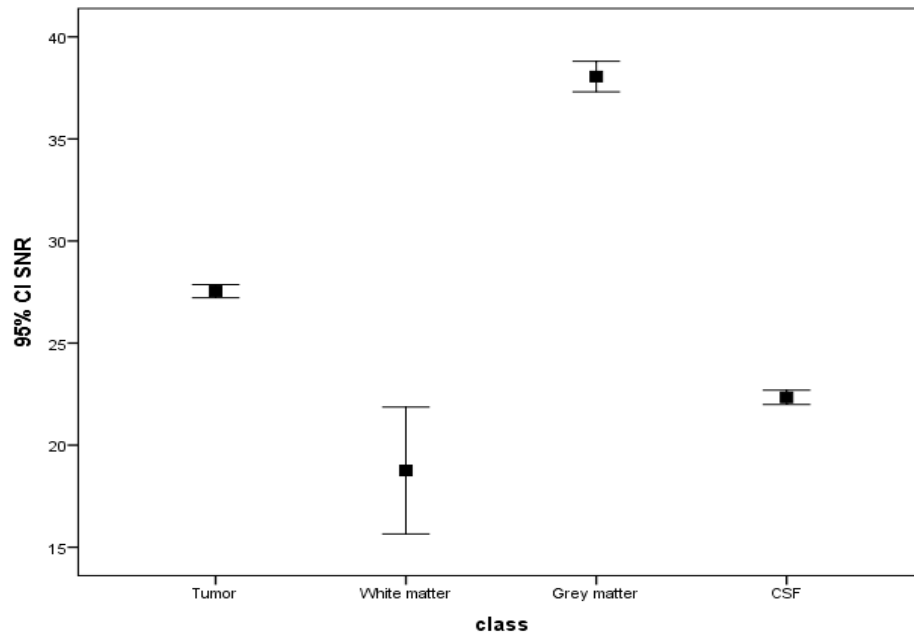


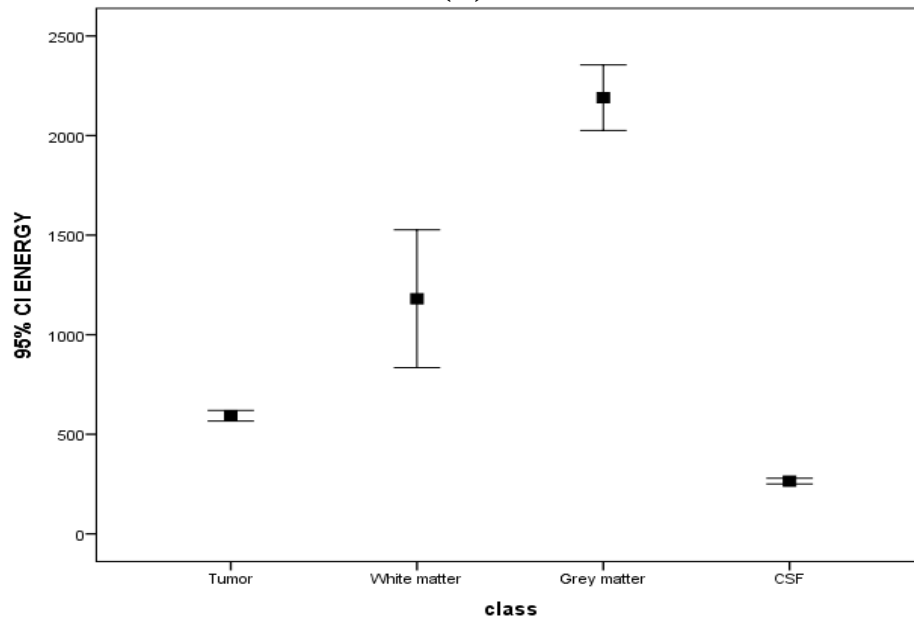
Figure 4-2 Scatter plot generated using discriminate analysis function for four .classes represents: white matter, grey matter, CSF and tumor

Table 4-1 classification score matrix generated by linear discriminate analysis for the scatter plot shown in Figure 4-2 with classification accuracy of 94.8%

Total	Predicted Group Membership				Original group	
	CSF	Grey matter	White matter	Tumor		
100%	2.7	0	0	<u>97.3</u>	Tumor	%
100%	1.7	2.6	<u>95.7</u>	0	White matter	
100%	0	<u>89.7</u>	5.1	5.1	Grey matter	
100%	<u>94.3</u>	0	0	5.7	CSF	
Total classification accuracy = 94.8%						

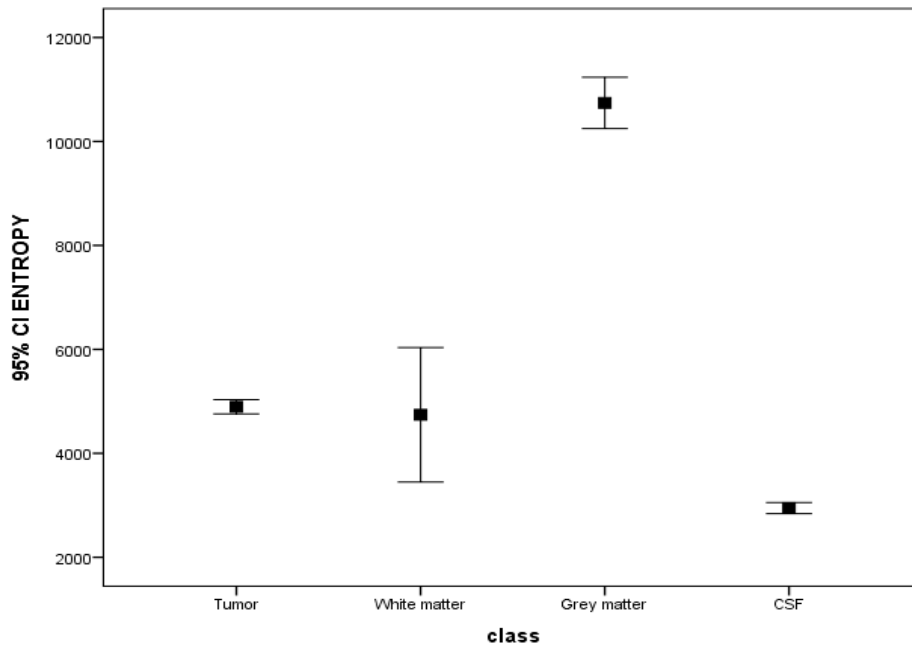


(A)

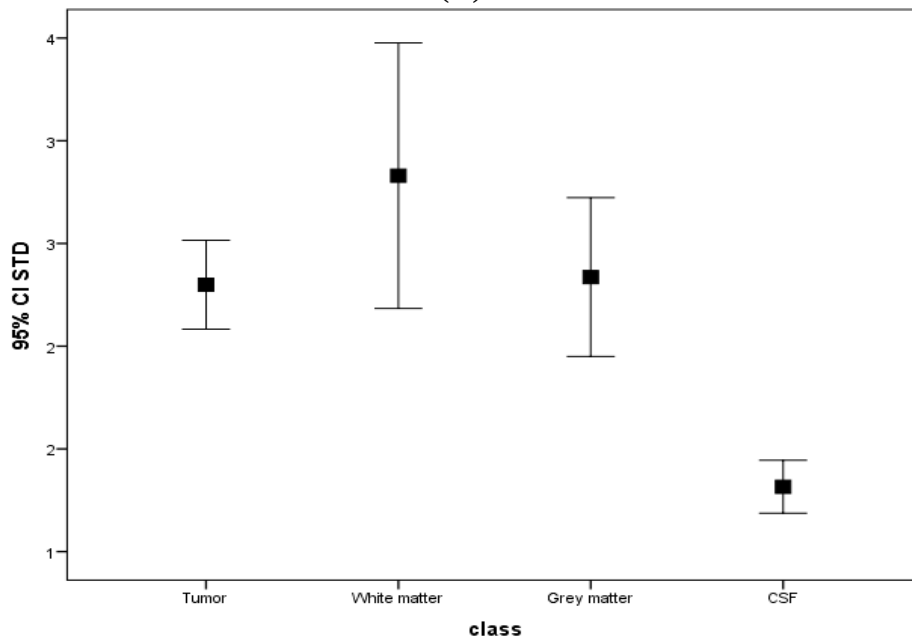


(B)

Figure 4-3 error bar plot for the (A) signal and (B) energy, textural features that selected by the linear stepwise discriminate function as a discriminate feature .where it discriminate between all features

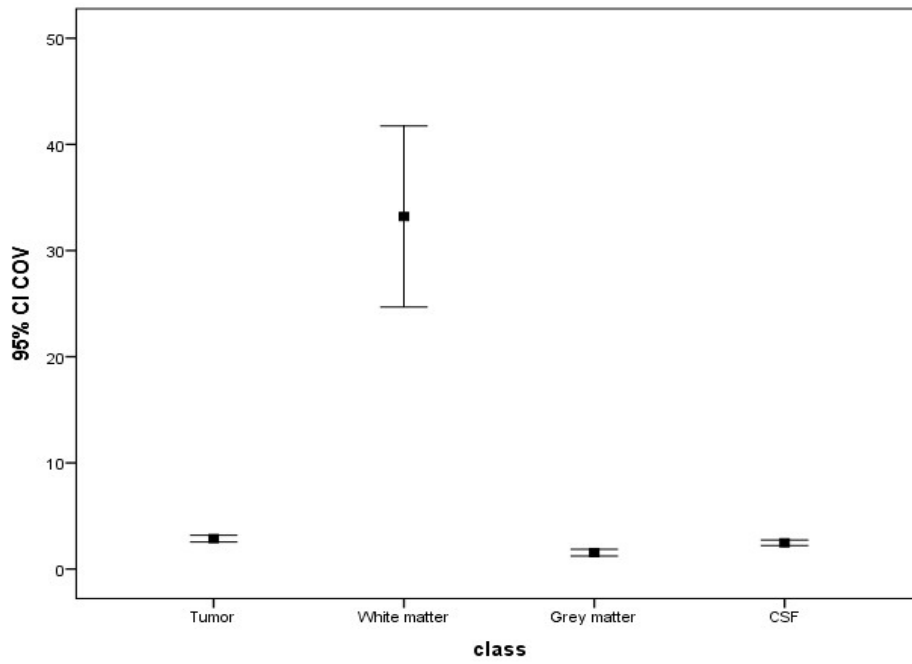


(A)

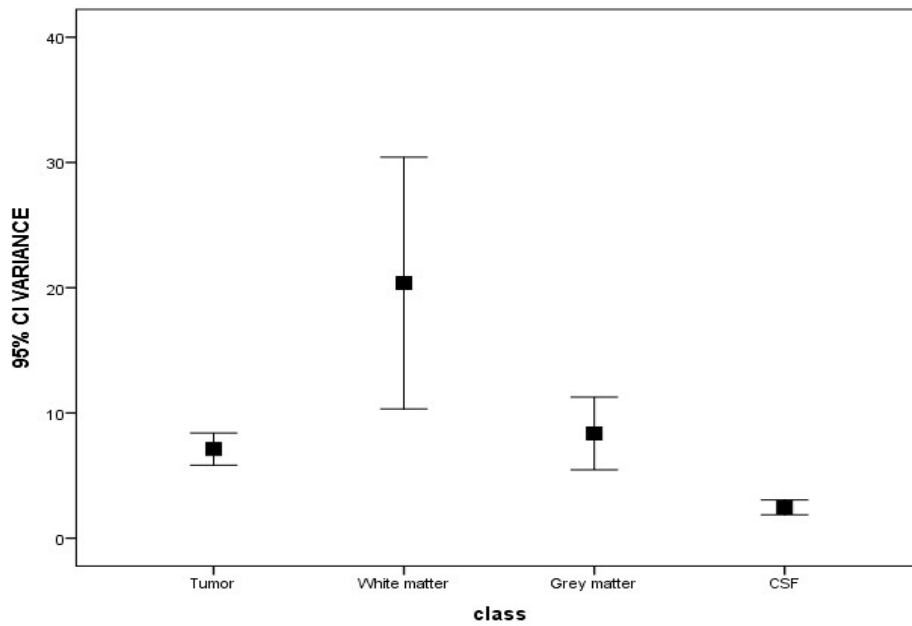


(B)

Figure 4-4 error bar plot for the (A) entropy and (B) standard deviation, textural features that selected by the linear stepwise discriminate function as a discriminate feature where in (A) it discriminate between gray matter and CSF .and in (B) between CSF and other features



(A)



(B)

Figure 4-5 error bar plot for the (A) coefficient of variation and (B) Variance, textural features that selected by the linear stepwise discriminate function as a discriminate feature where in (A) it discriminate between white matter and the rest of the classes .(B) between CSF, white matter and the rest of the classes

Chapter five

Discussion, conclusion and recommendation

The main aim of this study was to classify the brain image in axial MRI images into normal brain tissues (white matter, grey matter, cerebra-spinal fluid 'CSF') and Tumor using k-means and linear discriminated analysis

Discussion 5.1

In this study there weresix features extracted from normal and abnormal (tumor) brain MRI images using 3×3 window. From these features, six of them showed significant correlation with the predefined classes (white matter, grey matter, cerebrospinal fluid and tumor) they includes coefficient of variation, stander deviation .,variance, signal, energy, and entropy

The classification maps as shown in Figure 4-1 were generated by using Euclidean distance, where the centre of the classes chosen arbitrary from areas represented the classes of interest white matter, grey matter, cerebrospinal fluid and tumor. The algorithm classified these tissues using the selected centers as initial guess then iterates five cycles in each cycle change the classes centers using the average value of each features allocated to the class. The changes in the class center were small fraction and start to approach zero change from the third iteration. This means each .(class centers represent the class of interest (Figure 4-1 B

To classify the grey and white matter including cerebrospinal fluid as normal and abnormal (tumor) the features of the classified regions of the whole images (as raw data) were classified further using linear discriminate analysis. The result of the classification showed that the tumor areas were classified well from the rest of the tissues although it has characteristics mostly similar to surrounding tissue (Figure 4-2) with a classification accuracy of 97.3%, while gray matter, While the white matter and CSF showed a classification .(accuracy of 89.7%, 95.7 and 94.3% respectively Table (4-1

From the discriminated power point of view in respect to the applied features the signal (SNR) can differentiate between all the classes successfully (Figure 4-3 A). Similarly the energy (Figure 4-3 B) showed the same discriminated power. Entropy can successfully differentiate between the CSF, gray matter from the rest of the tissues but it does not show any variation between the other tissues; because the white matter has larger standard deviation compared to the average in respect to other tissues, so this situation lead to reduce the discriminated power between the tumor and white matter (Figure 4-4 A) while standard deviation feature differentiate well between the CSF and the rest of the tissue, where CSF showed lower variation than other tissue

The coefficient of variation discriminates between the white matter and the rest of the tissue (Figure 4-5 A), where all tissues showed low COV but white matter had inflated value, similar result achieved by the textural variable .(variance (Figure 4-5 A

In summary tumor and other brain tissues in MRI images for simplicity can be diagnosed as normal or abnormal by using the following simple equation after extracting the associated features

using a window of 3×3 pixel from the region of interest; the biggest classification score assume the tissue type

$$\textbf{Tumor} = (0.602 \times \text{COV}) + (-.126 \times \text{variance}) + (-4.349 \times \text{STD}) + (17.195 \times \text{SNR}) + (0.00008 \times \text{energy}) - .061 \times \text{entropy} - 109.37$$

$$\textbf{White matter} = (.511 \times \text{COV}) + (-.033 \times \text{variance}) + (-3.106 \times \text{STD}) + (13.146 \times \text{SNR}) + (.0001 \times \text{energy}) - .057 \times \text{entropy} + -54.627$$

$$\textbf{Grey matter} = (.496 \times \text{COV}) + (-.133 \times \text{variance}) + (-2.671 \times \text{STD}) + (12.576 \times \text{SNR}) + (.000046 \times \text{energy}) - .040 \times \text{entropy} + -74.131$$

$$\textbf{CSF} = (.645 \times \text{COV}) + (-.063 \times \text{variance}) + (-5.739 \times \text{STD}) + (19.374 \times \text{SNR}) + (0.00012 \times \text{energy}) - .076 \times \text{entropy} - 119.124$$

Conclusion 5.2

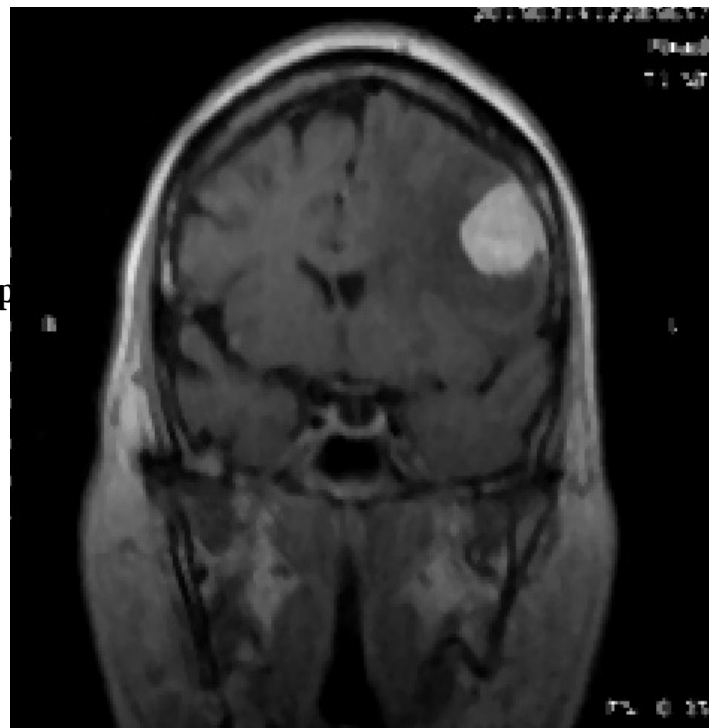
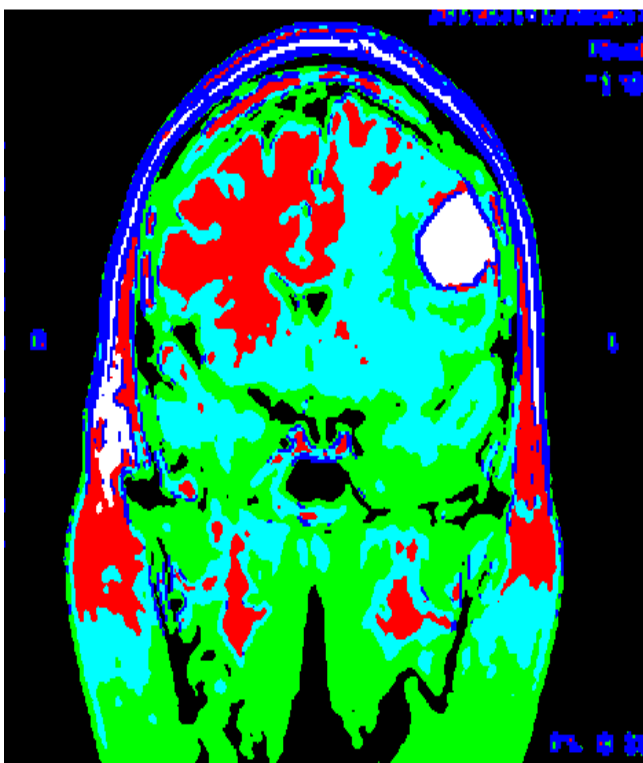
This study aim to segmente and classify the brain MRI imagesas normal tissuesand tumor (abnormal) using image processing technique, therefore multible feature of first order statistic were included: coefficent of variation,mean, stander devition,varince, .signal, energy and entropy

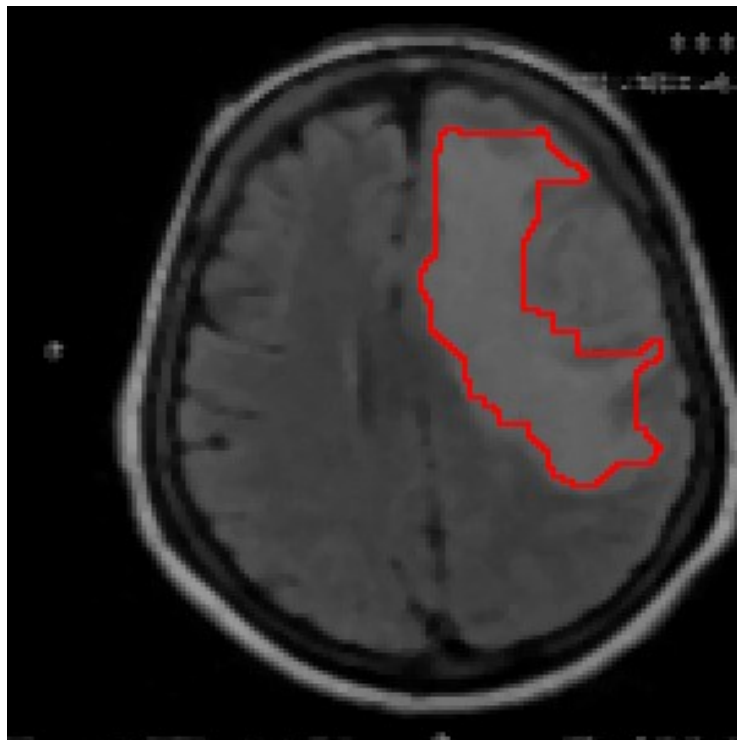
The study found that the tumor texture reveal a very differend underlying pattern compared to the other tissues of the brain.The classification accuracy of the tumor was 97.3% with overall .acurecy of 94.8% using linear discriminant analysis

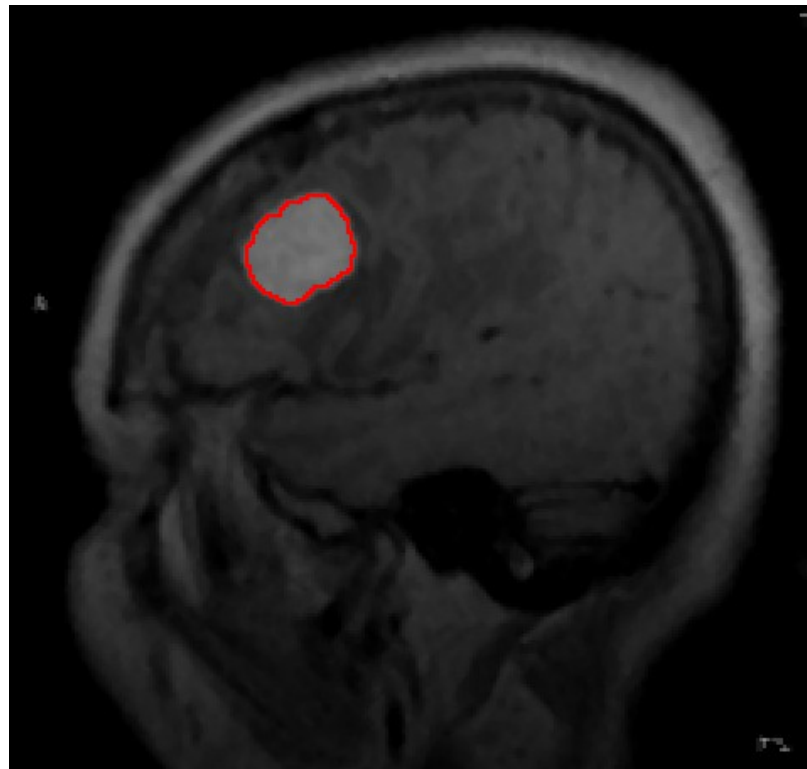
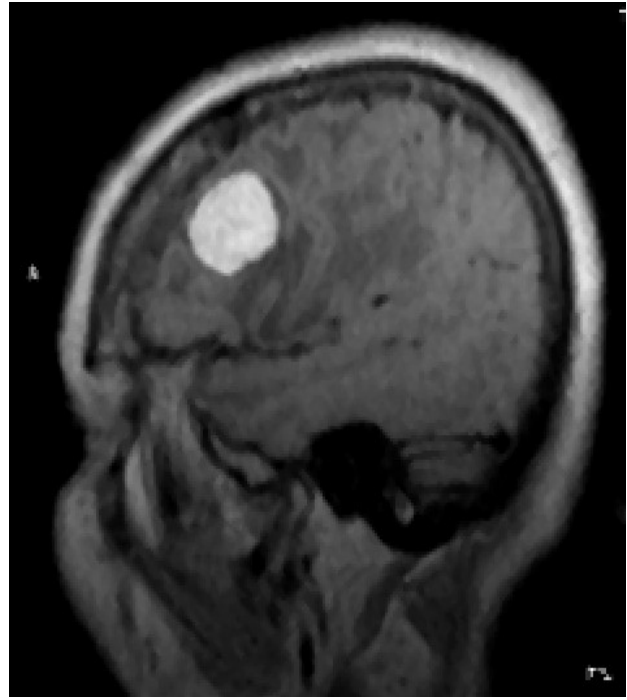
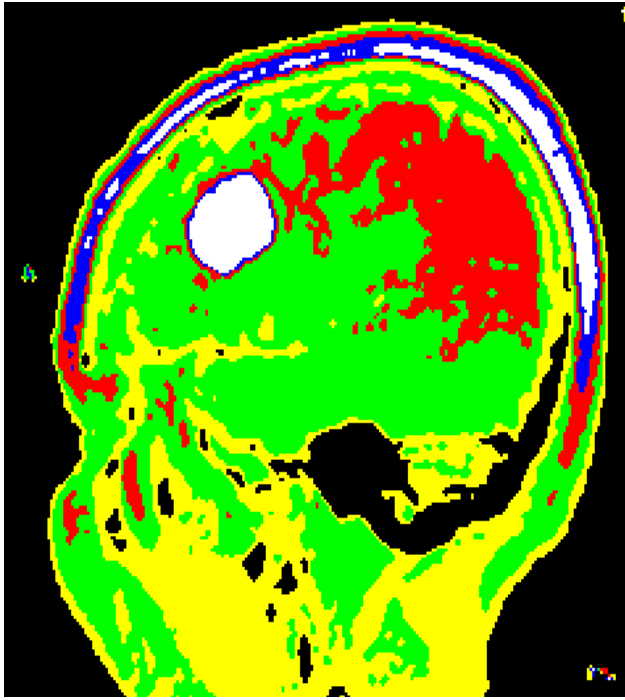
This study dictate that texture analysis is superior to visual perception system where texture reveals the change and the difference of the image pattern objectively in respect to the ground .truth

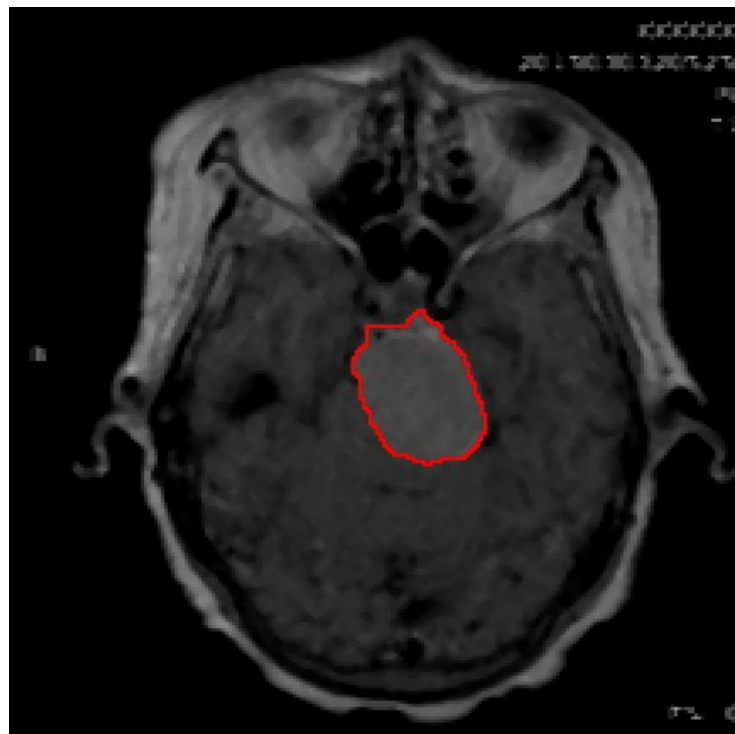
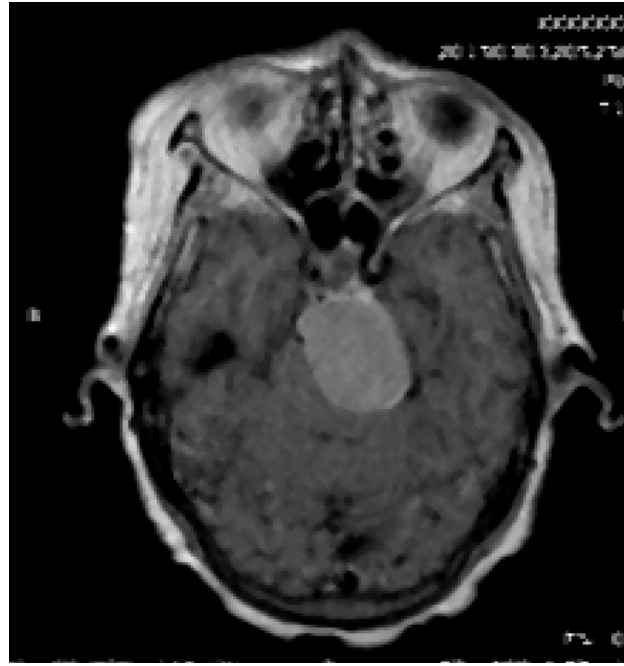
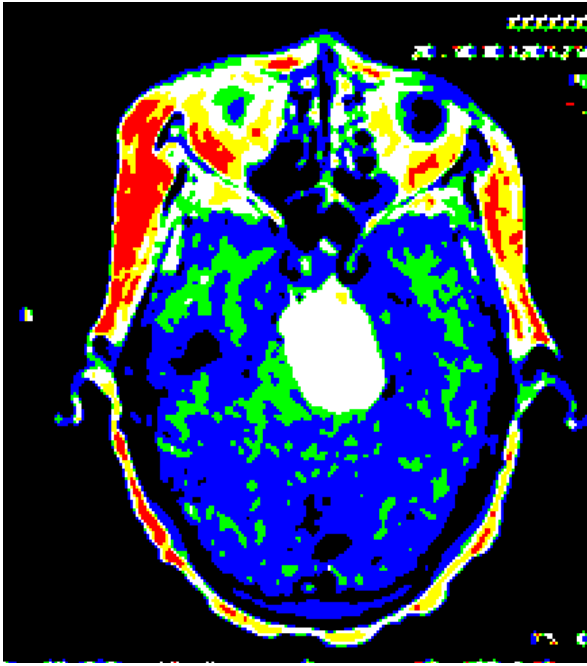
Recommendations 5-3

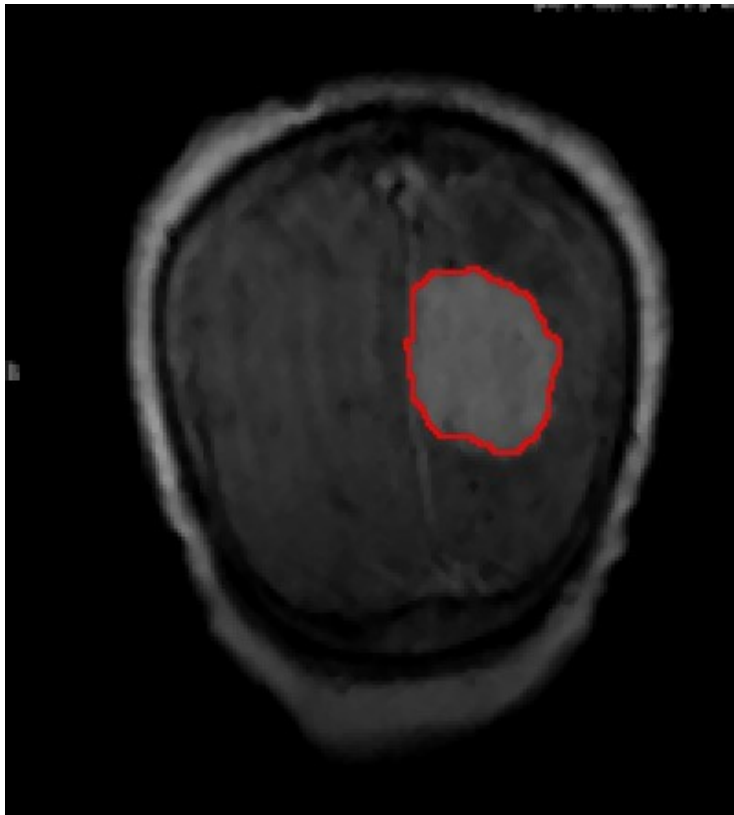
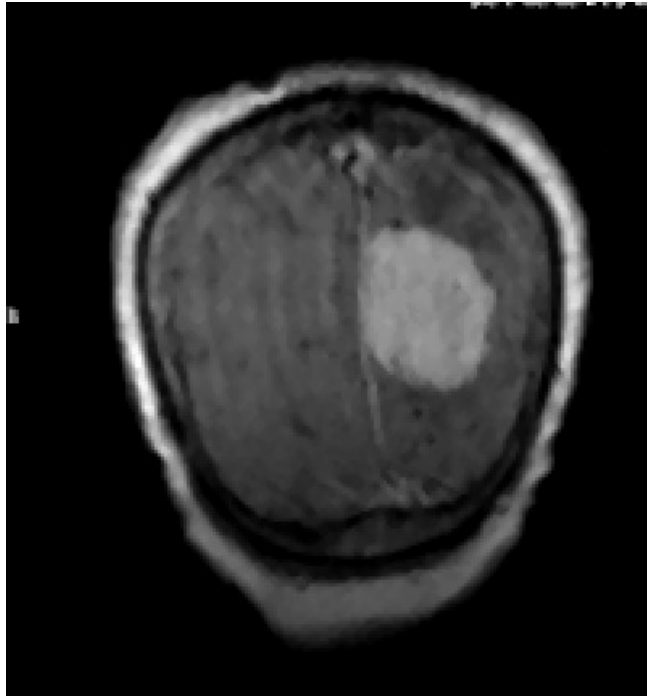
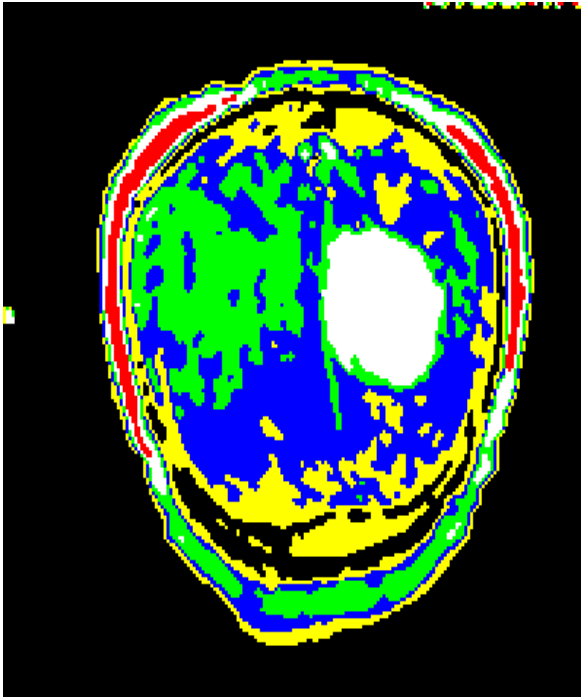
- Texture analysis can be carried out in all axial image where the tumour were visible in order to delineate the tumor outline .for rendering or having the volume of the tumor
- Further study could be done to differentiate between the type of brain tumours
- Adoption of such type of program by radiology department can facilitate a lot of useful information about the region of interest
- Initiation of image processing unit in the radiology department .can help a lot in activation of image processing projects

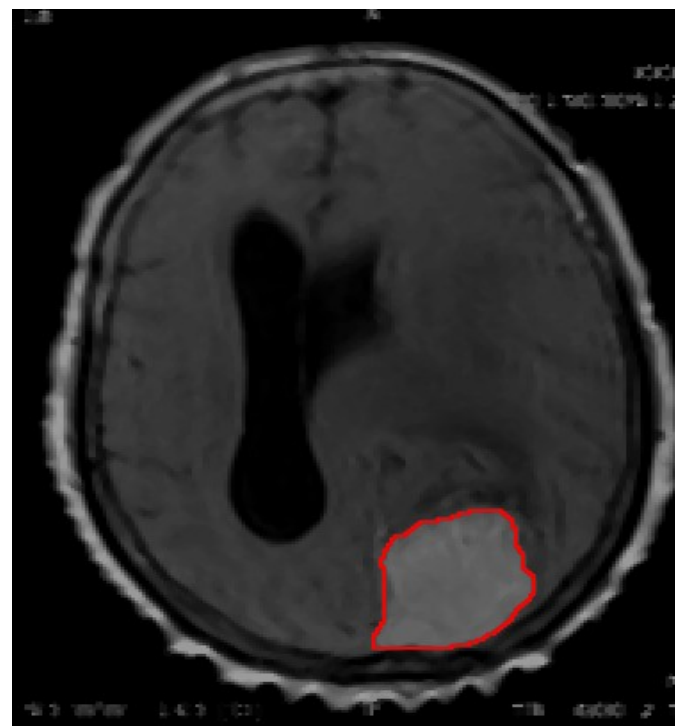
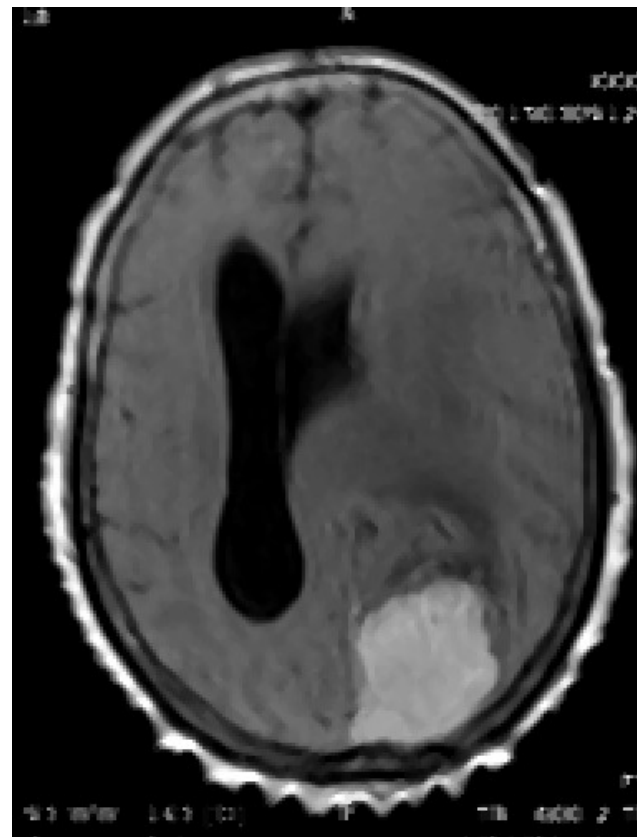
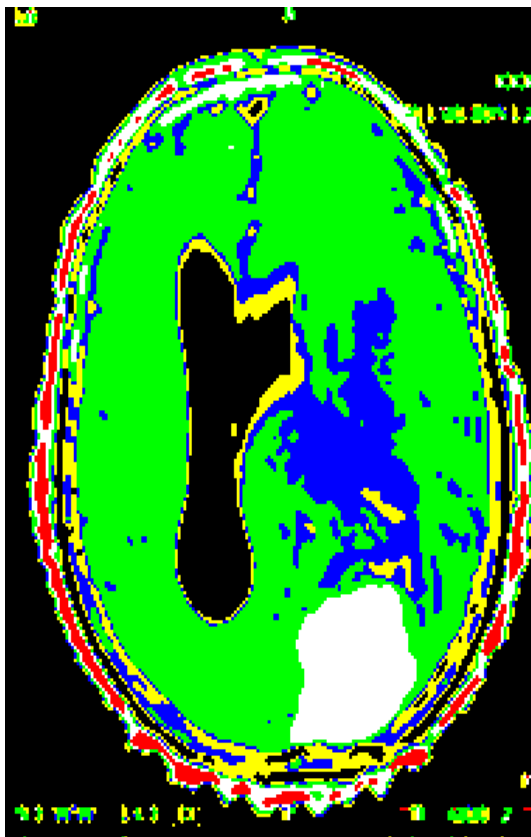


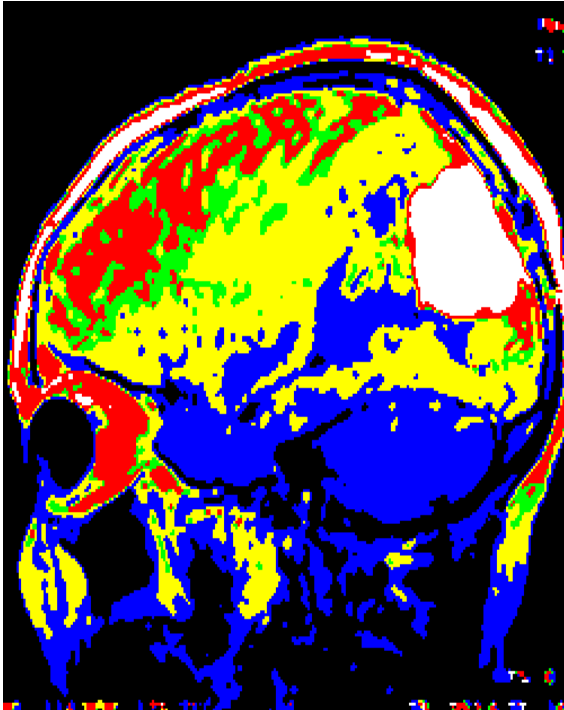


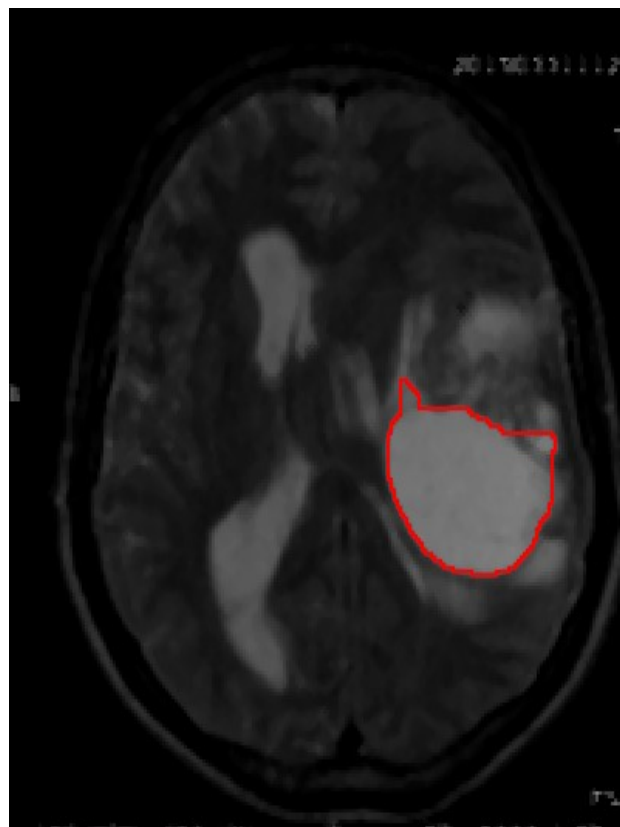
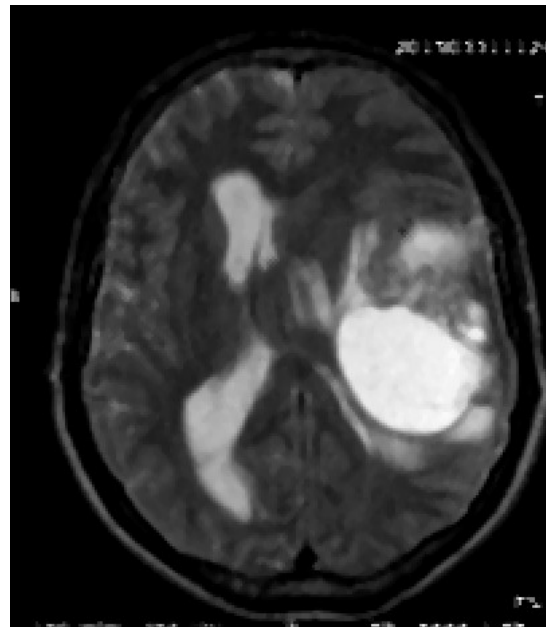
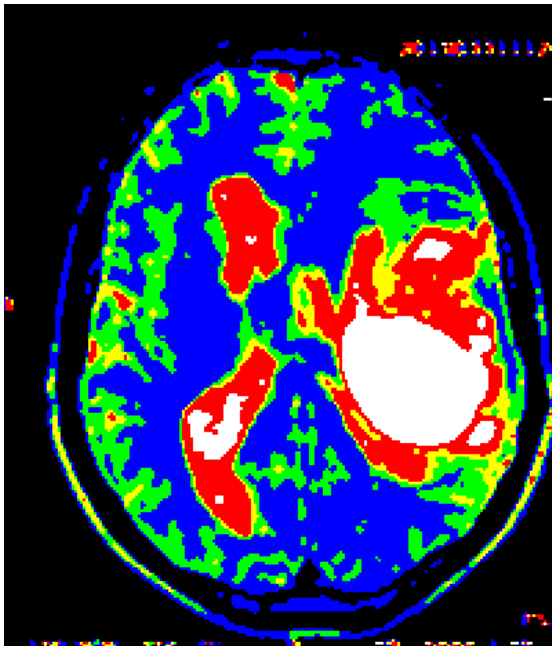


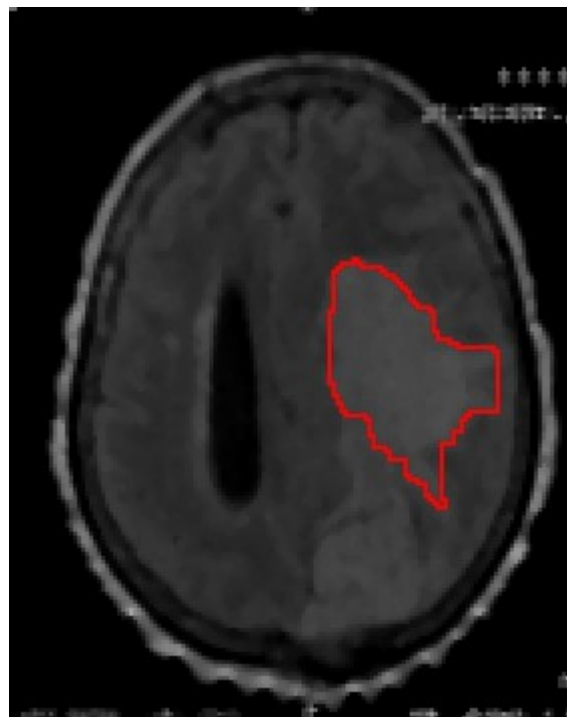
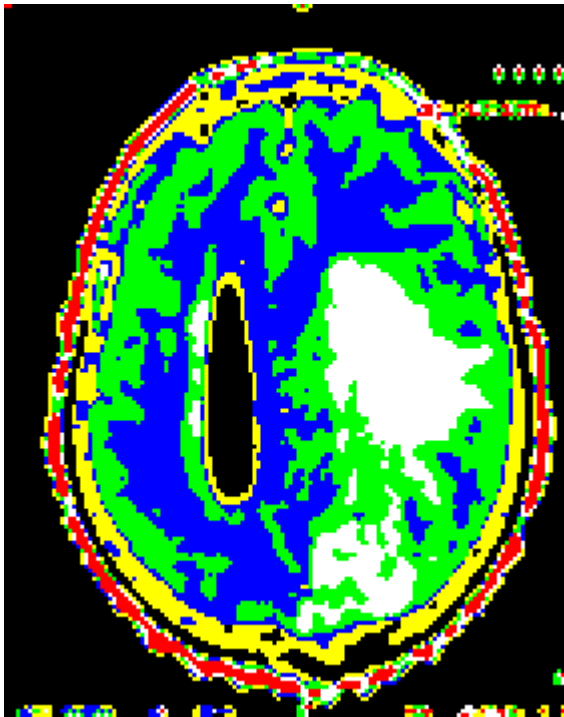


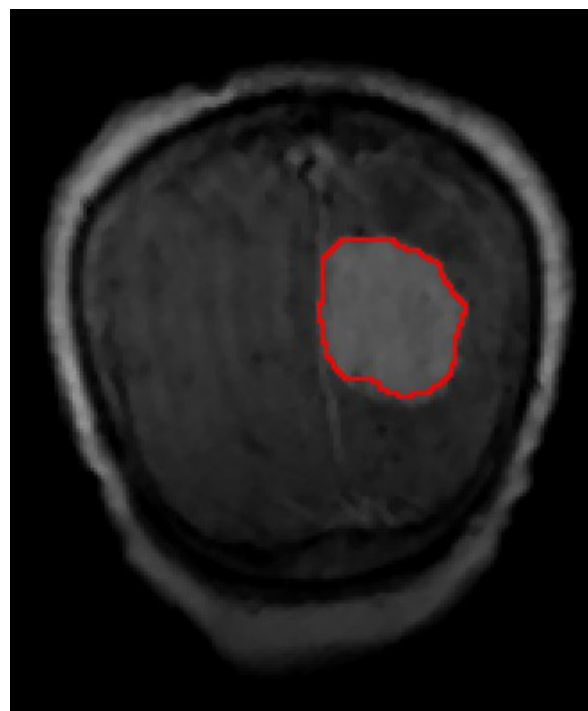
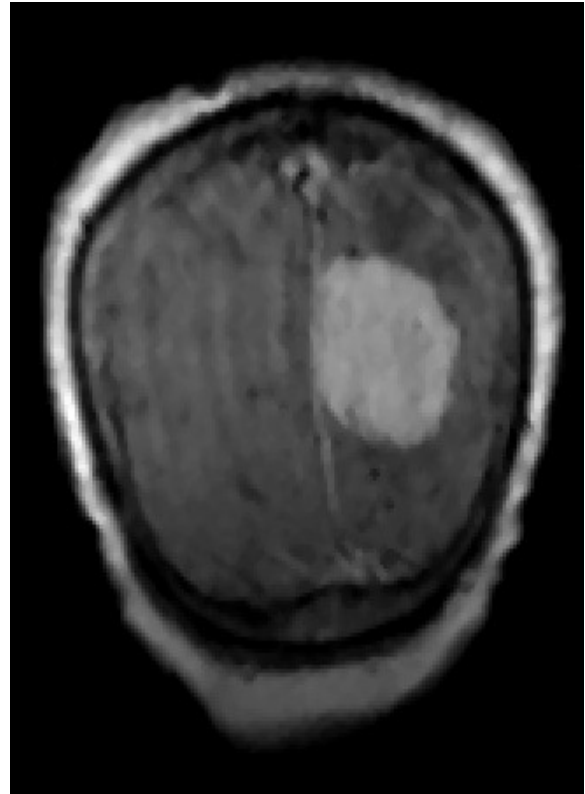
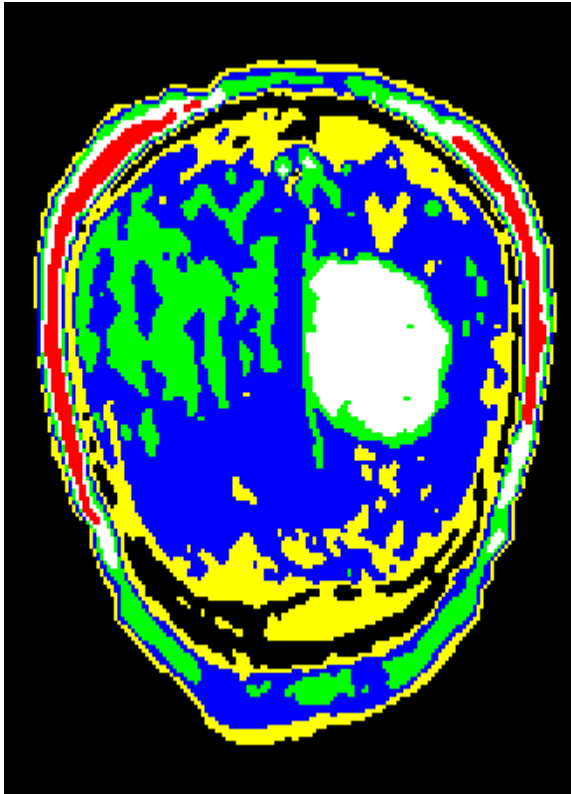


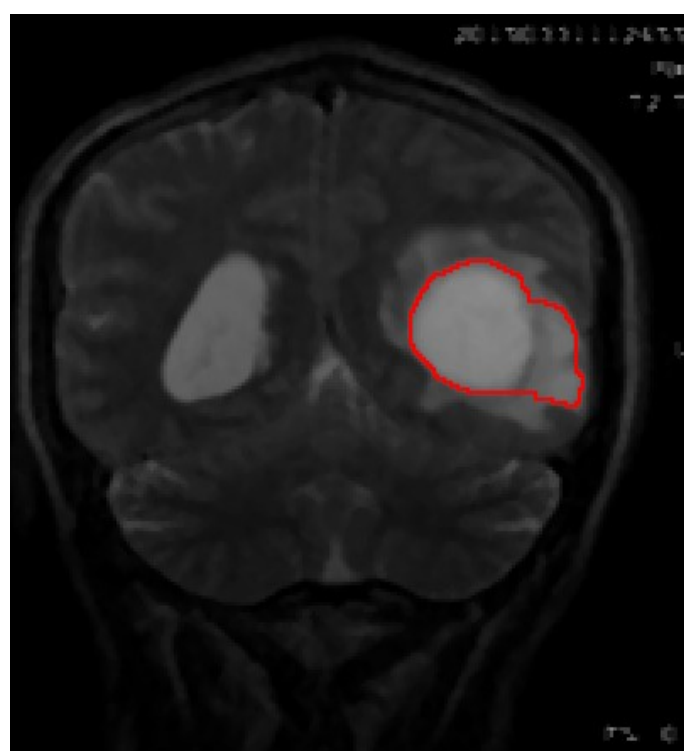
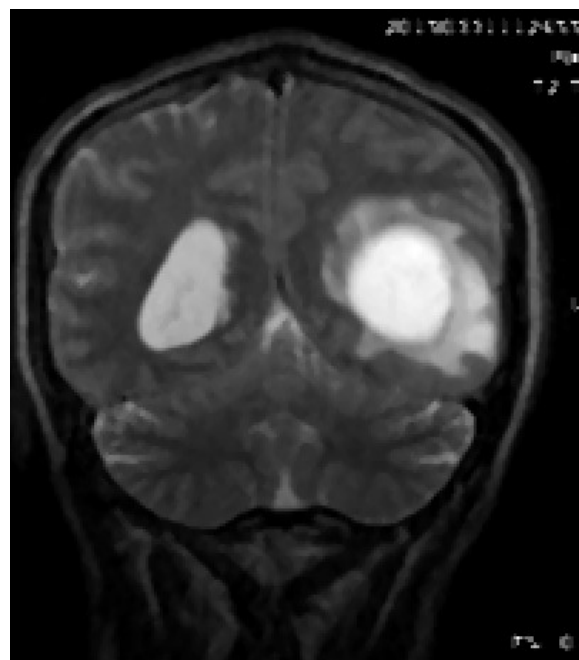
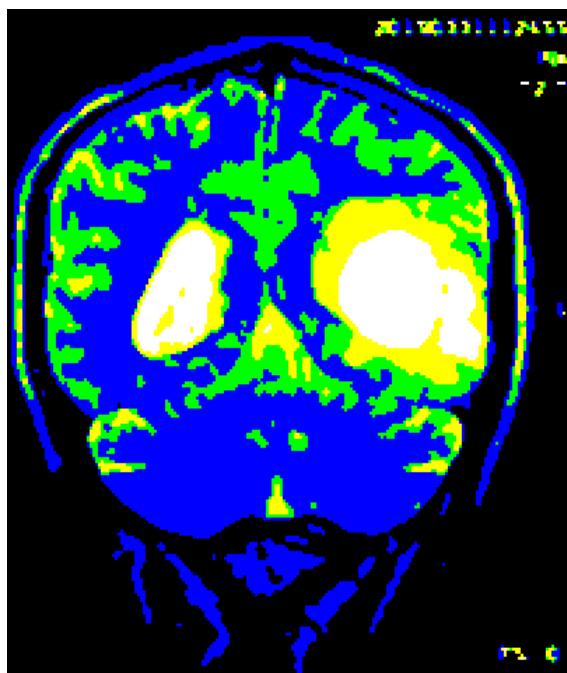












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