Brain Tumor Detection Using Clustering Technique

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CERTIFICATE OF APPROVAL

This is to certify that the project titled "**Brain Tumor Detection Using Clustering Technique**" carried out by **ISITA CHANDRA** (Roll No. **11714216002,** Registration No. **161170410011** of 2016-2017) for the partial fulfillment of the requirements for M.Tech degree in **Electronics and Communication Engineering** from **Maulana Abul Kalam Azad University of Technology, West Bengal** is absolutely based on his own work under the supervision of Dr**. SOHAM SARKAR**. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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DECLARATION

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CERTIFICATE of ACCEPTANCE

This is to certify that the project titled "**Brain Tumor Detection Using Clustering Technique**" carried out by **ISITA CHANDRA** (Roll No. **11714216002,** Registration No. **161170410011** of 2016-2017) is hereby recommended to be accepted for the partial fulfillment of the requirements for M.Tech degree in **Electronics and Communication Engineering** from **Maulana Abul Kalam Azad University of Technology, West Bengal**

Name of the Examiner Signature with Date

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ABSTRACT

Brain tumor is one of the major causes of death among other types of the cancers. Proper and timely diagnosis can prevent the life of a person to some extent. The purpose of this report is to detect the brain tumor and extract the tumor using clustering techniques. It can be considered as the most essential and crucial process for facilitating the delineation, characterization, and visualization of regions of interest in any medical image. Despite intensive research, segmentation remains a challenging problem due to the diverse image content, cluttered objects, occlusion, image noise, non-uniform object texture, and other factors. There are many algorithms and techniques available for image segmentation but still there needs to develop an efficient, fast technique of medical image segmentation. As a initial step first collect MRI brain image of HG (High Grade) and LG (Low grade) of different parts of brain like T1, T2, flair and grey matter. Here in this project an attempt is made to identify the affected regions by employing a very popular color image segmentation scheme called mean shift clustering. The efficiency of the algorithm is tested on challenging The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS 2012) dataset. Moreover different combinations of channels are used to form a color image and detect the tumor location.

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Chapter-1

1.1 Introduction:

Image segmentation refers to the process of partitioning a digital image into multiple regions. The goal of segmentation is to change the representation of an image to be more meaningful and easier to analyze. It is used in order to locate objects and boundaries in images. The result of image segmentation occurs as a set of regions that collectively covers the entire image. Therefore, medical image segmentation plays a significant role in clinical diagnosis. It can be considered as a difficult problem because medical images commonly have poor contrasts, different types of noise, and missing or diffusive boundaries. The anatomy of the brain can be scanned by Magnetic Resonance Imaging (MRI) scan or computed tomography (CT) scan. The MRI scan is more comfortable than CT scan for diagnosis. It is not affect the human body because it does not use any radiation. It is based on the magnetic field and radio waves. On the other hand, brain tumor is one of the leading causes of death among people. It is evidence that the chance of survival can be increased if the tumor is detected correctly at its early stage. In most cases, the physician gives the treatment for the strokes rather than the treatment for the tumor. Therefore, detection of the tumor is essential for the treatment. The lifetime of the person who affected by the brain tumor will increase if it is detected early. Thus, there is a need for an efficient medical image segmentation method with some preferred properties such as minimum user interaction, fast computation, accurate, and robust segmentation results.

On the other hand, image segmentation algorithms are based on one of the two fundamental properties of image intensity values: discontinuity and similarity. In the formal category, the segmentation approach is based on partitioning the processed image based on changes in intensity, such as edges and corners. The second one is based on partitioning an image into regions that are similar due to a set of predefined criteria. Therefore, there are many segmentation techniques which can be broadly used, such as histogram based methods, edge-based methods, artificial neural network based segmentation methods, physical model based approaches, region-based methods (region splitting, growing, and merging), and clustering methods (Fuzzy C-means clustering, K-means clustering, Mean Shift, and Expectation Maximization).

There are many challenging issues to image segmentation like development of a unified approach that can be applied to all types of images and applications. Even, the selection of an appropriate technique for a particular kind of image is a difficult problem. Thus, there is no universal accepted method for image segmentation. So, it remains a challenging problem in image processing and computer vision fields.

One view of image segmentation is a clustering problem that concerns how to determine which pixels in an image belong together most appropriately. There is an extensive literature on the methods that perform image segmentation based on clustering techniques. These methods usually show clustering in one of the two different ways, either by partitioning or by grouping pixels. In partitioning, the whole image is divided into regions that are good according to some criteria. Whereas in the grouping, the pixels are collected together based on some assumptions that determine how to group preferably. There are many clustering algorithms that can be used in image segmentation process, such as hard clustering or K-means clusters, and Fuzzy clustering. Therefore, clustering is a challenging field. It can be used as a stand-alone tool to gain insight into the distribution of data in different clusters for further analysis. Cluster analysis serves as a pre-processing step for other algorithms, such as classification that would then operate on detected clusters.

In this project we select three type of images T1, T2 and flair from BRATS 2012 and after that convert from gray scale to RGB, L*a*b* and Ycbcr color code by taking the six different combination of T1, T2 and flair.

After converting into these pseudo color code we follow some preprocessing techniques like we use average filter to smooth the image by reducing the amount of intensity variation between one pixel and next and also reduce noise. After that apply morphological open close operation for extracting image components and also apply after segmentation to remove imperfections introduced during segmentation. Image segmentation was done using Mean Shift Clustering for locating the maxima of density function given discrete data sampled from that function.

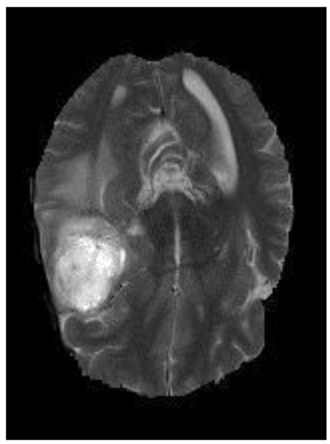


Fig-1: Example of an MRI showing the presence of tumor in brain.

A brain tumor is a collection, or mass, of abnormal cells in your brain. Your skull, which encloses your brain, is very rigid. Any growth inside such a restricted space can cause problems. Brain tumors can be cancerous (malignant) or noncancerous (benign). When benign or malignant tumors grow, they can cause the pressure inside your skull to increase. This can cause brain damage, and it can be life-threatening.

1.2 Literature Review:

Medical image segmentation is considered as a hot research topic. Several researchers have suggested various methodologies and algorithms for image segmentation. For example, Bandhyopadhyay and Paul *et al.* 2015 proposed a brain tumor segmentation method based on K-means clustering technique. The method consists of three steps: K-means algorithm based segmentation, local standard deviation guided grid based coarse grain localization, and local standard deviation guided grid based fine grain localization. The extraction of the brain tumor region from the processed image requires the segmentation of the brain MRI images to two segments. One segment contains the normal brain cells consisting of Grey Matter (GM), White Matter (WM), and the Cerebral Spinal Fluid (CSF). The second segment contains the tumor cells of the brain. The segmentation technique is constraint by the fact that the images need to be of adjacent imaging layer. The image fusion method gave a good result in fusing multiple images. In particular cases, it resulted in the loss of intensity. Moreover, it also ignored the finer anatomic details, such as twists and turns in the boundary of the tumor or overlapping region of gray and white matters in the brain.

Meena and Raja *et al.* 2013 proposed an approach of Spatial Fuzzy C-means (PET-SFCM) clustering algorithm on Positron Emission Tomography (PET) scan image datasets. The algorithm is joining the spatial neighborhood information with classical FCM and updating the objective function of each cluster. Spatial relationship of neighboring pixel is an aid of image segmentation. These neighboring pixels are highly renovated the same feature data. In spatial domain, the memberships of the neighbor centered are specified to obtain the cluster distribution statistics. They calculated the weighting function based on these statistics and applied into the membership function.

Their algorithm is tested on data collection of patients with Alzheimer's disease. They did not calculate objective based quality assessment that could analyze images and did not report their quality without human involvement.

Glavan and Holban *et al.* 2015 proposed system that using a convolution neural network (CNN) as pixel classifier for the segmentation process of some X-ray images. The system analyzes each pixel from the image and tries to classify them into two classes: bone and non-bone. They attempted to separate the bone tissue area from the rest of the image. Their CNN obtained the best results in contrast to other configurations. For ensuring a minimum training time of the network, they used only the interest areas from an image. Their method recognized the significant bone areas, but the problems appeared when the bone area presented irregularities and take more execution time in training.

Tatiraju and Mehta *et al.* 2015 introduced image segmentation using K-means clustering, Expectation Maximization (EM), and Normalized Cuts (NC). They analyzed the two former unsupervised learning algorithms and compared them with a graph-based algorithm, the Normalized Cut algorithm. They applied the partitioning algorithm to gray-scaled images with varying value of K (number of clusters). For smaller values of K, the K-means and EM algorithms give good results. For larger values of K, the segmentation is very coarse; many clusters appear in the images at discrete places. The NCuts algorithm gave good results for larger value of K, but it takes a long time.

Yerpude and Dubey *et al.* 2012 proposed color image segmentation using K-Medoids Clustering. The idea of the algorithm is to find clusters of objects by finding the Medoids for each cluster. Each remaining object is clustered with the Medoid or representative objects to which it is the most similar. K-Medoids method uses representative objects as reference points rather than taking the mean value of the objects in each cluster. The algorithm takes the input parameter K and the number of clusters to be partitioned among a set of N objects. The segmented images are highly dependent on the number of segments or centers. They did not consider finding optimal number of segments to provide more accurate results.

Islam and Ahmed *et al.* 2015 proposed image segmentation technique based on K-means, K-Mediods, and Hierarchical clustering technologies. They made a comparison between these three clustering techniques on natural images to find the advantages and disadvantages of each algorithm. After applying these algorithms, they mentioned that the K-means Clustering method has better performance and easy to implement than other clustering methods.

On the other hand, other several researchers have suggested various hybrid algorithms for image segmentation. For example, Christe *et al.* 2015 made the integration between K-means and Fuzzy C-means. They chose the number of clusters, fuzziness, distance, and stopping the criterion. Then, they initialized the memberships randomly or getting from K-means and in iterations, recalculating centers and memberships until the objective function reached. The advantage of their method is that it can deal with overlapping grayscale intensities. The disadvantage of their proposed method is that it cannot clearly defined borders between tissues successfully. Although, it minimizes the within-class sum square errors, but its performance degrade when applied to noise corrupted images. They solved this problem by the preprocessing step before applying the integration. They compared their result with KM, FCM, and the integration FKM in case of under-segmentation and over-segmentation. They proved that FKM gives minimum under or over-segmentation, but they did not demonstrate what about time of each algorithm or in the integration method.

Funmilola *et al.* 2012 made the Fuzzy K-C-means method, which carries more of Fuzzy C-means properties than that of K-means. The algorithm reads the image, determines the iterations, reduces the iterations by distance checker, gets the size of the image, concatenates the dimension, generates large data items with distance calculation, and reduces repetition when possible distance has been attained. The iteration begins by identifying significant component of data then it stops when possible identification elapses. Fuzzy K-C-means works on grayscale images like Fuzzy C-means. It generates the same number of iterations as in Fuzzy C-means. The authors reduced the iterations by checking the distances only. The disadvantage is that the result of their proposed method is similar to the outcome of the Fuzzy C-means algorithm except in some images.

Chapter-2

2.1 Types of Tumor:

Tumor

The word tumor is a synonym for a word neoplasm which is formed by an abnormal growth of cells Tumor is something totally different from cancer. There are three common types of tumor:

1) Benign
2) Pre-Malignant
3) Malignant

Benign Tumor

A benign tumor is a tumor is the one that does not expand in an abrupt way; it doesn't affect its neighboring healthy tissues and also does not expand to non-adjacent tissues. Moles are the common example of benign tumors.

Pre-Malignant Tumor

Premalignant Tumor is a precancerous stage, considered as a disease, if not properly treated it may lead to cancer.

Malignant Tumor

Malignancy (mal- = "bad" and -ignis = "fire") is the type of tumor, that grows worse with the passage of time and ultimately results in the death of a person. Malignant is basically a medical term that describes a severe progressing disease. Malignant tumor is a term which is typically used for the description of cancer.

2.2 Image Segmentation:

In computer vision, image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super-pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s). When applied to a stack of images, typical in medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like Marching cubes.

2.2.1 Application:

Some of the practical applications of image segmentation are:

- Content-based image retrieval
- Machine vision
- Medical imaging, including volume rendered images from computed tomography and magnetic resonance imaging.
- Locate tumors and other pathologies
- Measure tissue volumes
- Diagnosis, study of anatomical structure
- Surgery planning
- Virtual surgery simulation
- Intra-surgery navigation
- Object detection
- Pedestrian detection
- Face detection
- Brake light detection
- Locate objects in satellite images (roads, forests, crops, etc.)
- Recognition Tasks
- Face recognition
- Fingerprint recognition
- Iris recognition
- Traffic control systems
- Video surveillance
- Several general-purpose algorithms and techniques have been developed for image segmentation. To be useful, these techniques must typically be combined with a domain's specific knowledge in order to effectively solve the domain's segmentation problems.

2.2.2 Different method of Image Segmentation:

Thresholding

The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image. There is also a balanced histogram thresholding.

The key of this method is to select the threshold value (or values when multiple-levels are selected). Several popular methods are used in industry including the maximum entropy method, Otsu's method (maximum variance), and k-means clustering.

Clustering methods

Clustering can be considered the most important unsupervised learning problem; so, as every other problem of this kind, it deals with finding a structure in a collection of unlabeled data. A
definition of clustering could be "the process of organizing objects into groups whose members are similar in some way". A cluster is therefore a collection of objects which are "similar" between them and are "dissimilar" to the objects belonging to other clusters.

Compression-based methods

Compression based methods postulate that the optimal segmentation is the one that minimizes, over all possible segmentations, the coding length of the data. The connection between these two concepts is that segmentation tries to find patterns in an image and any regularity in the image can be used to compress it. The method describes each segment by its texture and boundary shape.

Histogram-based methods

Histogram-based methods are very efficient compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image. Color or intensity can be used as the measure.

A refinement of this technique is to recursively apply the histogram-seeking method to clusters in the image in order to divide them into smaller clusters. This operation is repeated with smaller and smaller clusters until no more clusters are formed.

Edge detection

Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have therefore been used as the base of another segmentation technique.

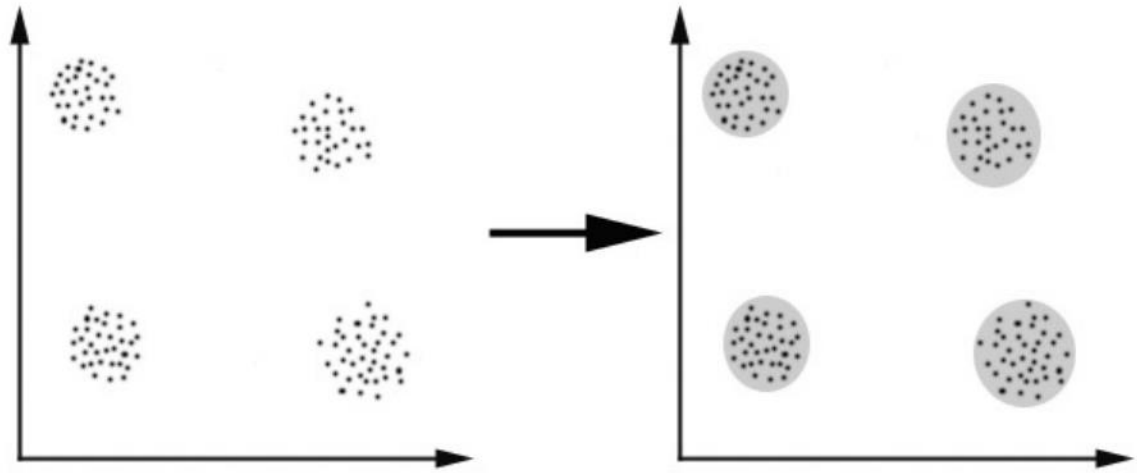
The edges identified by edge detection are often disconnected. To segment an object from an image however, one needs closed region boundaries. The desired edges are the boundaries between such objects or spatial-taxons.

Region-growing methods

Region growing methods rely mainly on the assumption that the neighboring pixels within one region have similar values. The common procedure is to compare one pixel with its neighbors. If a similarity criterion is satisfied, the pixel can be set to belong to the cluster as one or more of its neighbors. The selection of the similarity criterion is significant and the results are influenced by noise in all instances**.**

2.3 Clustering:

Clustering is a process of collection of objects which are similar between them while dissimilar
objects belong to other cluster.
Image clustering and categorization is a means for high level description of image content. The
goal is to fnd a mapping of the archive images into classes (Clusters) such that the set of classes
provide essentially the same information about the image archive as the entire image set collection.
The common approach to image clustering involves addressing the following issues:
1. Image features- hoe to represent the image.
2. Organization of feature data- how to organize the data.
3. Classifier- how to classify an image to a certain cluster.
Clustering can be considered the most important unsupervised learning problem; so, as every
other problem of this kind, it deals with finding a structure in a collection of unlabeled data.



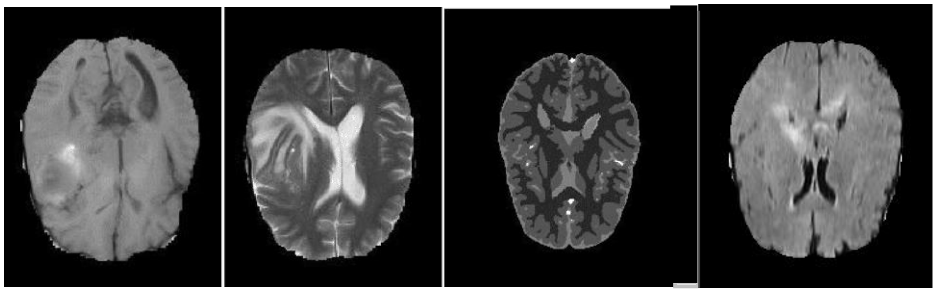
(a) **(b)**

Fig-2: (a) distance- based clustering, (b) conceptual clustering

In this case we easily identify the 4 clusters into which the data can be divided ,the similarity
criterion is distance: two or more objects belong to the same cluster if they are "close " according
to a given distance. This is called **distance- based clustering.**

Another kind of clustering is **conceptual clustering** two or more objects belong to the same
cluster if this one defnes a concept common to all that objects. In other words, objects are
grouped according to their ft to descriptive concepts, not according to simple similarity measures.

2.4 Magnetic Resonance MRI Images:



(a) (b) (c) (d)

Fig-3: (a) T1, (b) T2, (c) Grey Matter, (d) Flair

Magnetic resonance imaging (MRI) is one of the most commonly used tests in neurology and neurosurgery. MRI provides exquisite detail of brain, spinal cord & vascular anatomy, and has the advantage of being able to visualize anatomy in three planes: axial, sagittal and coronal (see the example image below).

MRI has an advantage over CT in being able to detect flowing blood and cryptic vascular malformations. It can also detect disease, and has no beam-hardening artifacts such as can be seen with CT. Thus, the posterior fosse is more easily visualized on MRI than CT. Imaging is also performed without any ionizing radiation.

Tissue can be characterized by two different relaxation times – T1 and T2.

T1 (longitudinal relaxation time) is the time constant which determines the rate at which excited protons return to equilibrium. It is a measure of the time taken for spinning protons to realign with the external magnetic field.

T2 (transverse relaxation time) is the time constant which determines the rate at which excited protons reach equilibrium or go out of phase with each other. It is a measure of the time taken for spinning protons to lose phase coherence among the nuclei spinning perpendicular to the main field.

Fluid Attenuated Inversion Recovery (Flair) is the Flair sequence is similar to a T2-weighted image except that the TE &TR times are very long. By doing so, abnormalities remain bright but normal CSF fluid is attenuated and made dark. This sequence is very sensitive to pathology & makes the differentiation between CSF and an abnormality much easier.

Grey Matter contains most of the brain's neuronal cell bodies. The grey matter includes regions of the brain involved in the muscle control, and sensory perceptions such as seeing and hearing, memory, emotions, speech, decision making and self control.

2.5 HG and LG:

Primary brain tumors are cancers that originate in the brain. These tumors are very different
from secondary brain tumors, which originally developed elsewhere in the body and spread
(metastasized) to the brain.
Primary brain tumors develop from glial cells. Glial cells provide the structural backbone of the
brain and support the function of the neurons (nerve cells), which are responsible for thought,

sensation, muscle control, and coordination.

Primary brain tumors are tumors that are classifed by a pathologist according to their appearance under the microscope. Gliomas are classifed into four grades (I, II, III and IV), and
the treatment and prognosis depend upon the tumor grade.

Grade I or II tumors are termed low-grade gliomas. The term malignant or high-grade glioma
refers to tumors that are classifed as:

●**Grade III** (anaplastic astrocytoma, anaplastic oligodendroglioma, anaplastic oligoastrocytoma,
anaplastic ependymoma)

●**Grade IV** (glioblastoma)

A glioma is a type of tumor that starts in the brain or spine. It is called a glioma because it arises
from glial cells. The most common site of gliomas is the brain. Gliomas make up about 30% of
all brain and central nervous system tumors and 80% of all malignant brain tumors.

The glial cells surround neurons and provide support for and insulation between them. Glial
cells are the most abundant cell types in the central nervous system.

2.5.1 Low Grade Glioma Symptoms

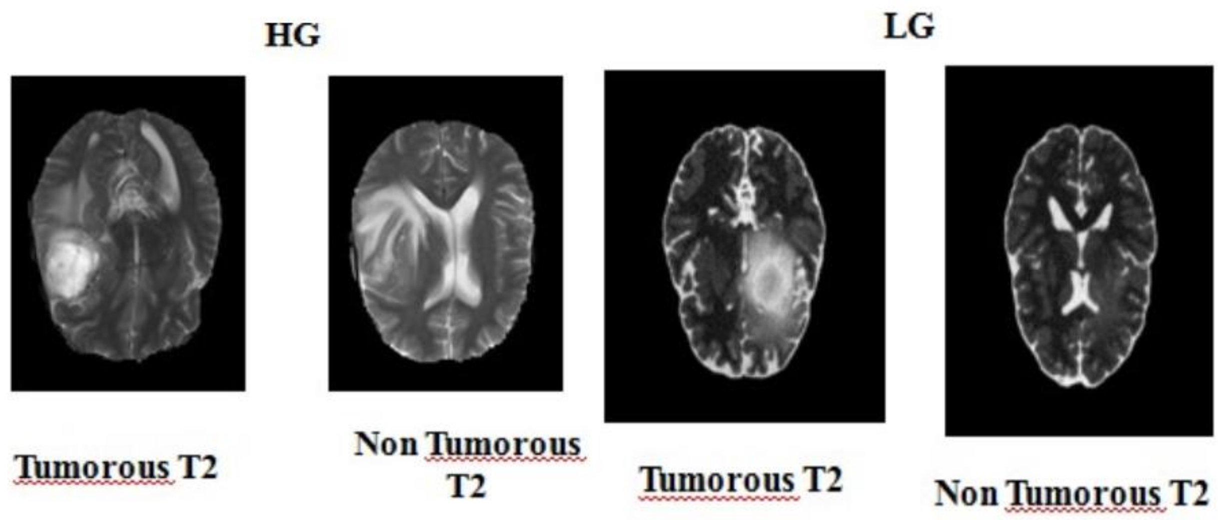
Low-grade gliomas do not spread outside the brain, but instead grow into the normal brain tissue, creating symptoms as the tumor grows locally. This can disrupt connections between normal brain cells and can also create pressure on the nearby brain. The brain cannot expand when there is a tumor growing within it since it is confned within the skull. As a result, even a relatively small, slow-growing tumor can cause severe brain problems, particularly if the tumor is in a critical area of the brain.

2.5.2 High-Grade Glioma Symptoms

Gliomas cause symptoms by invading (growing) into and/or creating pressure in nearby
normal brain tissue. The most common symptoms include:

- Cognitive symptoms like memory loss, personality change, confusion, speech problems
- Headache
- Seizures – Seizures occur in more than one-half of patients with grade III gliomas and about

one-fourth of patients with grade IV gliomas. Seizures are caused by disorganized electrical
activity in the brain. Medications are usually necessary to control seizures.
Other common symptoms of brain tumors include muscle weakness, visual symptoms, and
changes in sensation.



(a) (b) (c) (d)

Fig-4: (a) HG Tumorous T2, (b) HG Non Tumorous T2, (c) LG Tumorous T2, (d) LG Non Tumorous T2

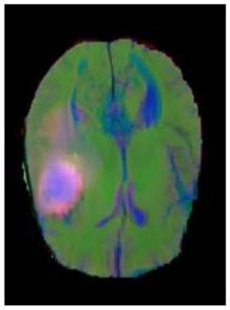
Chapter-3

3.1 Morphological Open-close operation:

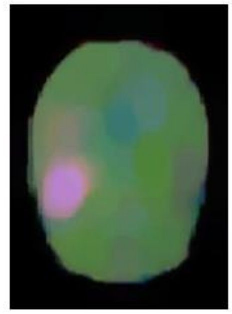
Opening and closing are two important operators from mathematical morphology. They are both derived from the fundamental operations of erosion and dilation. Like those operators they are normally applied to binary images, although there are also graylevel versions. The basic effect of an opening is somewhat like erosion in that it tends to remove some of the foreground (bright) pixels from the edges of regions of foreground pixels. However it is less destructive than erosion in general. As with other morphological operators, the exact operation is determined by a structuring element. The effect of the operator is to preserve foreground regions that have a similar shape to this structuring element, or that can completely contain the structuring element, while eliminating all other regions of foreground pixels.

Closing is an important operator from the field of mathematical morphology. Like its dual operator opening, it can be derived from the fundamental operations of erosion and dilation. Like those operators it is normally applied to binary images, although there are graylevel versions. Closing is similar in some ways to dilation in that it tends to enlarge the boundaries of foreground (bright) regions in an image (and shrink background color holes in such regions), but it is less destructive of the original boundary shape. As with other morphological operators, the exact operation is determined by a structuring element. The effect of the operator is to preserve background regions that have a similar shape to this structuring element, or that can completely contain the structuring element, while eliminating all other regions of background pixels.

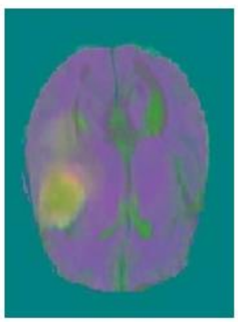
3.1.1 Outputs of Morphological Open Close Operation:



(a)

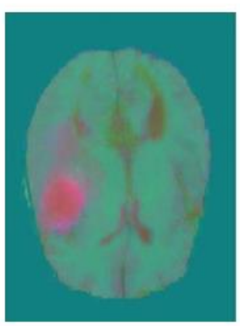


(b)



(c)

(d)



(e)

(f)

Fig-5: (a) Original Image (RGB), (b) Morphological open close (RGB), (c) Original Image (L*a*b*), (d) Morphological open close (L*a*b*), (e) Original Image (YCbCr), (d) Morphological open close (YCbCr)

3.2 Mean-Shift Clustering:

Mean shift is a non-parametric feature-space analysis technique for locating the maxima of a density function, a so-called mode-seeking algorithm. Application domains include cluster analysis in computer vision and image processing.

Mean shift is a procedure for locating the maxima—the modes—of a density function given discrete data sampled from that function. This is an iterative method, and we start with an initial estimate x. Let a kernel function $K(x_i - x)$ be given. This function determines the weight of nearby points for re-estimation of the mean. Typically a Gaussian kernel on the distance to the current estimate is used, the weighted mean of the density in the window determined by K is

$$m(x) = \frac{\sum_{x_i \in N(x)} K(x_i - x)x_i}{\sum_{x_i \in N(x)} K(x_i - x)}$$

where **N (x)** is the neighborhood of **x**, a set of points for which **K (x)** $\neq 0$. The difference **m (x) – x** is called **mean shift** in Fukunaga and Hostetler. The mean-shift algorithm now sets **x ← m (x)** , and repeats the estimation until m (x) converges.

Although the mean shift algorithm has been widely used in many applications, a rigid proof for the convergence of the algorithm using a general kernel in a high dimensional space is still not known. Aliyari Ghassabeh showed the convergence of the mean shift algorithm in one-dimension with a differentiable, convex, and strictly decreasing profile function. However, the one-dimensional case has limited real world applications. Also, the convergence of the algorithm in higher dimensions with a finite number of the (or isolated) stationary points has been proved. However, sufficient conditions for a general kernel function to have finite (or isolated) stationary points have not been provided.

3.2.1 The Mean shift Algorithm:

I will need a few things before you start to run Meanshift on a set of datapoints X:

1. A function N(x) to determine what are the neighbours of a point x ∈ X. The neighbouring points are the points within a certain distance. The distance metric is usually Euclidean Distance.
2. A kernel K(d) to use in Meanshift. K is usually a Gaussian Kernel, and d is the distance between two datapoints.

Now, with the above, this is the Meanshift algorithm for a set of datapoints X:

1. For each datapoint x ∈ X, find the neighbouring points N(x) of x.
2. For each datapoint x ∈ X, calculate the mean shift m(x) from this equation:

$$m(x) = \frac{\sum_{x_i \in N(x)} K(x_i - x) x_i}{\sum_{x_i \in N(x)} K(x_i - x)}$$

3. For each datapoint x ∈ X, update x ← m(x).
4. Repeat 1. for n_iteations or until the points are almost not moving or not moving.

The formula in step 2. looks daunting but let's break it down. Notice the red red encircled parts are essentially the same:

$$m(x) = \frac{\boxed{\sum_{x_i \in N(x)} K(x_i - x)} x_i}{\boxed{\sum_{x_i \in N(x)} K(x_i - x)}}$$

Let's replace that with Wi, so the formula becomes this:

$$m(x) = \frac{\sum_i \mathbf{W_i}\, x_i}{\sum_i \mathbf{W_i}}$$

The general formula for weighted average

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

The most important piece is calculating the mean shift m(x). The algorithm finds a set of nearby points that affect a datapoint, then shift it towards where most of the points are, and the closest points have more influence than the further points. Repeat this for all datapoints until nothing changes.

3.3 Average Filter:

Average (or mean) filtering is a method of 'smoothing' images by reducing the amount of intensity variation between neighbouring pixels. The average filter works by moving through the image pixel by pixel, replacing each value with the average value of neighbouring pixels,

including itself. There are some potential problems:

1. A single pixel with a very unrepresentative value can significantly affect the average value of all the pixels in its neighbourhood.
2. When the filter neighbourhood straddles an edge, the filter will interpolate new values for pixels on the edge and so will blur that edge. This may be a problem if sharp edges are required in the output.

3.3.1 3 by 3 Average filtering:

1. Consider the following 3 by 3 average filter

$$\begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix}$$

2. We can write mathematically as:

$$I\_new(x,y) = \sum_{j=-1}^{1} \sum_{i=-1}^{1} 1 \times I\_old(x+i, y+j)$$

$$I\_new\_normalized(x,y) = \frac{1}{\sum_{j=-1}^{1} \sum_{i=-1}^{1} 1} \sum_{j=-1}^{1} \sum_{i=-1}^{1} 1 \times I\_old(x+i, y+j)$$

3.4 Regional Maxima:

An image can have multiple regional maxima or minima but only a single global maxima or minima. Determining image peaks or valleys can be used to create marker images that are used in morphological reconstruction.

The imregionalmax and imregionalmin functions identify all regional minima or maxima.

For example, this simple image contains two primary regional maxima, the blocks of pixels containing the value 13 and 18, and several smaller maxima, set to 11.

```
A = [10    10    10    10    10    10    10    10    10    10;
     10    13    13    13    10    10    11    10    11    10;
     10    13    13    13    10    10    10    11    10    10;
     10    13    13    13    10    10    11    10    11    10;
     10    10    10    10    10    10    10    10    10    10;
     10    11    10    10    10    18    18    18    10    10;
     10    10    10    11    10    18    18    18    10    10;
     10    10    11    10    10    18    18    18    10    10;
     10    11    10    11    10    10    10    10    10    10;
     10    10    10    10    10    10    11    10    10    10]
```

The binary image returned by imregionalmax pinpoints all these regional maxima.

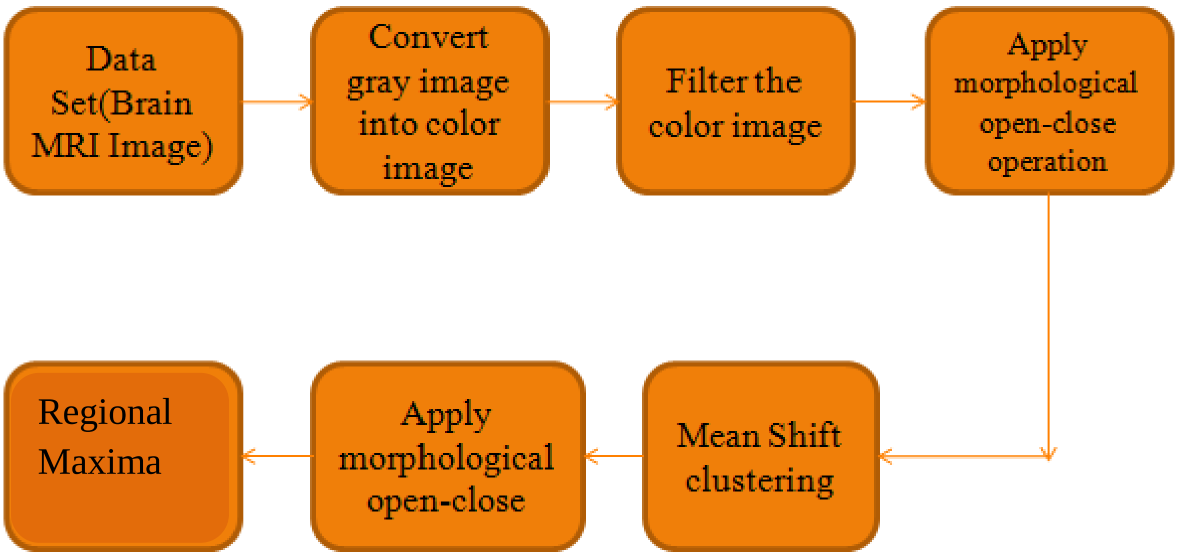
B = imregionalmax(A)

```
B =
     0     0     0     0     0     0     0     0     0     0
     0     1     1     1     0     0     1     0     1     0
     0     1     1     1     0     0     0     1     0     0
     0     1     1     1     0     0     1     0     1     0
     0     0     0     0     0     0     0     0     0     0
     0     1     0     0     0     1     1     1     0     0
     0     0     0     1     0     1     1     1     0     0
     0     0     1     0     0     1     1     1     0     0
     0     1     0     1     0     0     0     0     0     0
     0     0     0     0     0     0     1     0     0     0
```

You may want to only identify areas of the image where the change in intensity is extreme; that is, the difference between the pixel and neighboring pixels is greater than (or less than) a certain threshold.

Chapter-4

4.1 Proposed Method:



In this project we select three type of brain images T1, T2 and flair from BRATS 2012.

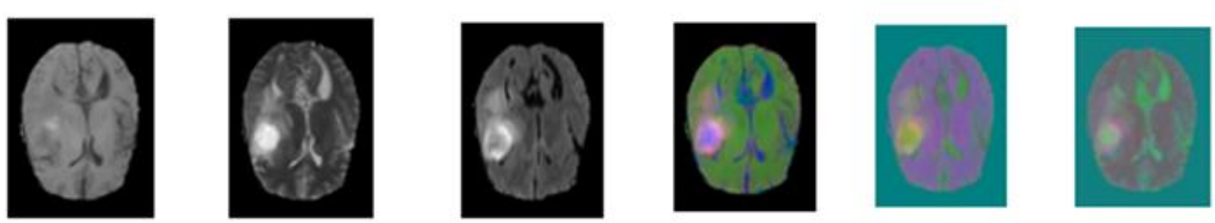
- After that convert grayscale image into RGB, L*a*b* and YCbCr color code by taking the six different combination of T1, T2 and flair. These pseudo color code have three channel so that six combination of T1, T2 and flair are inserted in these three channel.
- After converting into these pseudo color code we follow some preprocessing techniques like we use average filter to smooth the image by reducing the amount of intensity variation between one pixel and next and also reduce noise.
- After that apply morphological open close operation for extracting image components. The basic effect of an opening is somewhat like erosion in that it tends to remove some of the foreground (bright) pixels from the edges of regions

of foreground pixels and remove small objects. Closing is similar in some ways to dilation in that it tends to enlarge the boundaries of foreground (bright) regions in an image (and shrink background color holes in such regions), but it is less destructive of the original boundary shape.

- Image segmentation was done using Mean Shift Clustering for locating the maxima of density function given discrete data sampled from that function. Mean Shift algorithm is a non-parametric clustering technique which does not require prior knowledge of the number of cluster and does not constrain the shape of the cluster.
- Again apply morphological open close operation to remove imperfections introduced during segmentation.
- Regional maxima is used to extract tumor region from the brain image.

4.2 Convert grayscale image into Color image:

For experimental results three brain MR image T1,T2 and flair are chosen from BRATS 2012 and combination of these three gray images are converted into RGB, L*a*b* and YCbCr.



(a) (b) (c) (d) (e) (f)

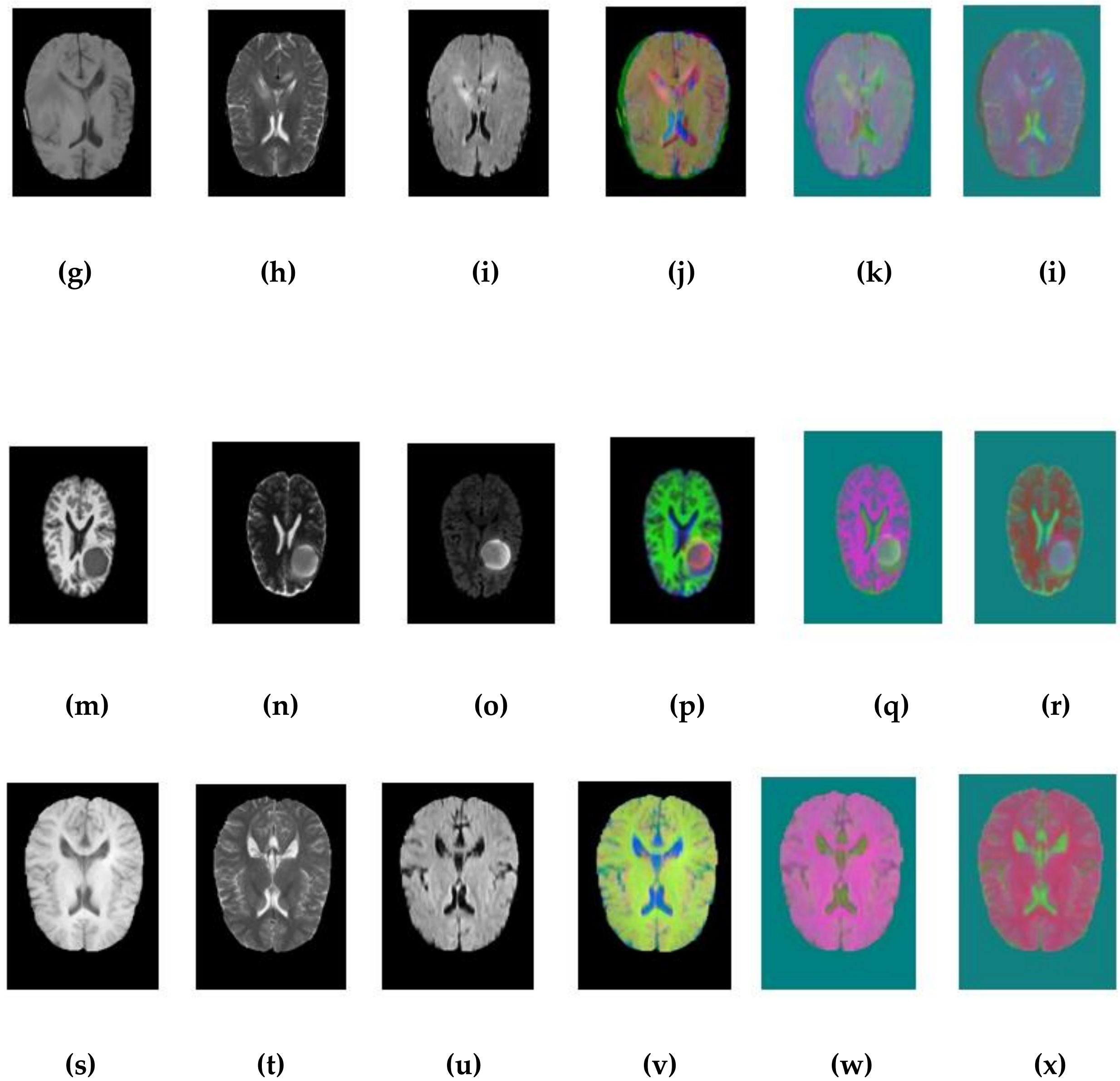


Fig-6: (a), (g), (m), (s)- T1; (b), (h), (n), (t)- T2; (c), (i), (o), (u)- flair; (d), (j), (p), (v)- RGB; (e), (k), (q), (w)- L*a*b*; (f), (i), (r), (x)- YCbCr

4.3 Six Combination of T1, T2 and Flair in RGB, L*a*b* and YCbCr

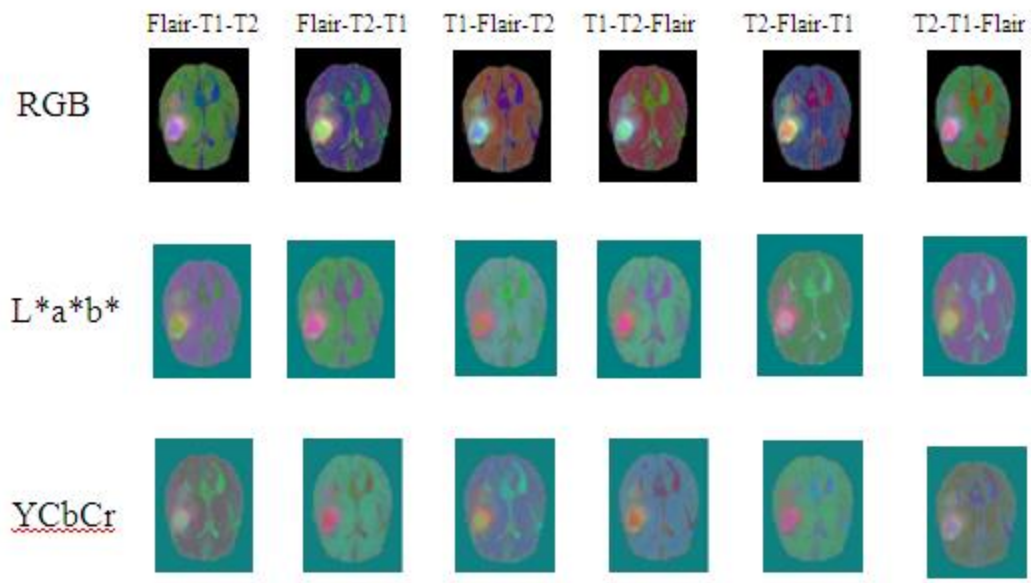


Fig-7: Six Combination of T1, T2 and Flair in RGB, L*a*b* and YCbCr

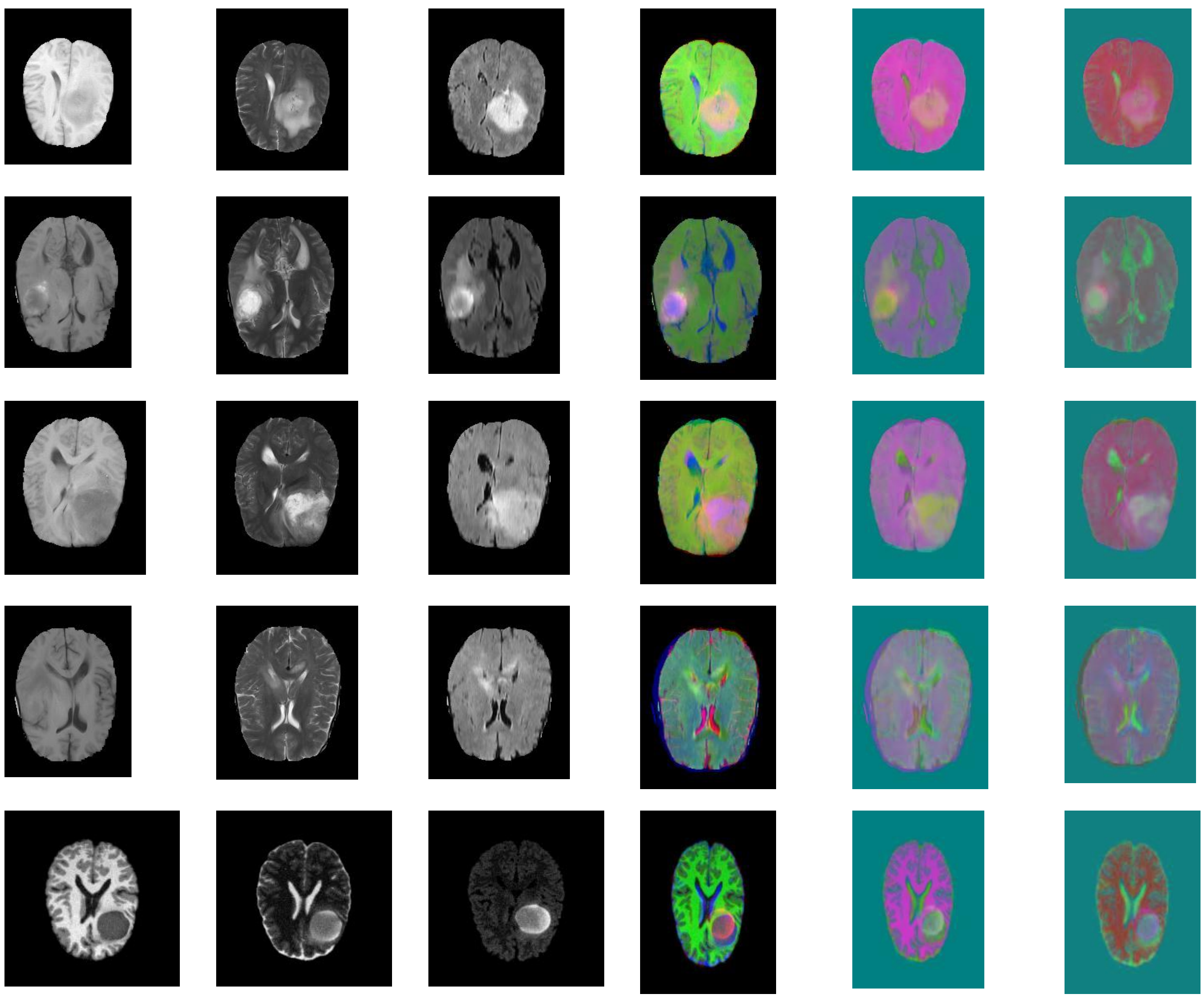
- Three brain images T1, T2 and Flair are chosen from BRATS 2012.
- RGB, L*a*b* and YCbCr are the pseudo color code and each color code has three channel like in RGB there are three channel R channel, G channel and B Channel, L*a*b* color code has L channel, a channel and b channel, YCbCr has Y channel, Cb channel and Cr channel.
- Now six combination of T1, T2 and flair like flair-T1-T2, flair-T2-T1, T1-flair-T2, T1-T2-flair, T2-flair-T1 and T2-T1-flair are inserted in these three channel of RGB, L*a*b* and YCbCr.

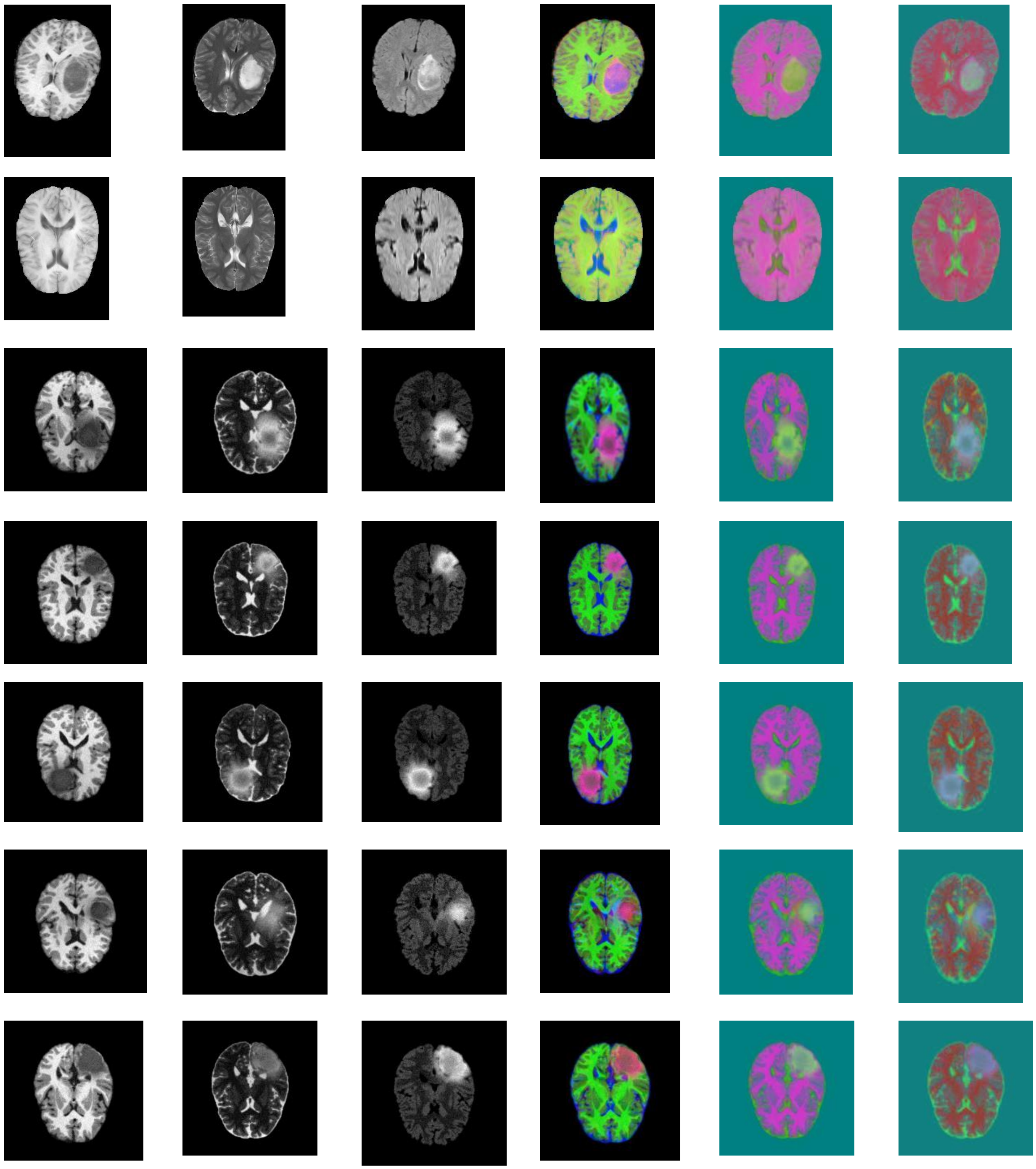
Chapter-5

5.1 Experimental Results:

Brain tumor detection using Mean shift clustering was performed in MATLAB 2012 in a workstation with Intel (R) Pentium (R) 2.13 GHz processor. For experimental results 12 brain MR images T1,T2 and flair are chosen from BRATS 2012 and convert into RGB, L*a*b* and YCbCr.

Combination-Flair+T1+T2

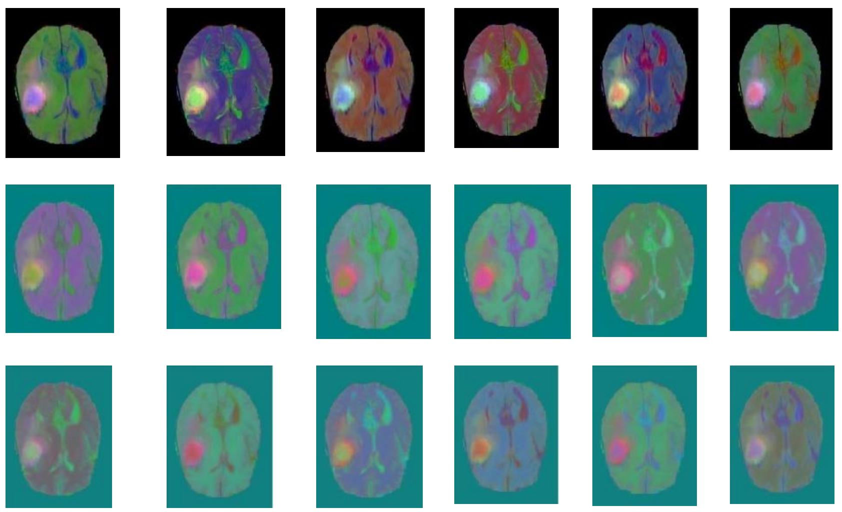




(a) (b) (c) (d) (e) (f)

Fig-8: (a) T1 of 12 sample images; (b) T2 of 12 sample images; (c) flair of 12 sample images; (d) RGB ; (e) L*a*b*, (f) YCbCr

Three brain images T1, T2 and Flair are chosen from BRATS 2012. RGB, L*a*b* and YCbCr are the pseudo color code and each color code has three channel like in RGB there are three channel R channel, G channel and B Channel, L*a*b* color code has L channel, a channel and b channel, YCbCr has Y channel, Cb channel and Cr channel. Now six combination of T1, T2 and flair like flair-T1-T2, flair-T2-T1, T1-flair-T2, T1-T2-flair, T2-flair-T1 and T2-T1-flair are inserted in these three channel of RGB, L*a*b* and YCbCr which is shown in fig-9



(a) (b) (c) (d) (e) (f)

Fig-9: (a) flair-T1-T2 in RGB, L*a*b* and YCbCr, (b) flair-T2-T1 in RGB, L*a*b* and YCbCr, (c) T1-flair-T2 in RGB, L*a*b* and YCbCr, (d) T1-T2-flair in RGB, L*a*b* and YCbCr, (e) T2-flair-T1 in RGB, L*a*b* and YCbCr, (f) T2-T1-flair in RGB, L*a*b* and YCbCr.

After converting into these pseudo color code we follow some preprocessing techniques like we use average filter to smooth the image by reducing the amount of intensity. After that apply morphological open close operation for extracting image components. Again apply morphological open close operation to remove imperfections introduced during segmentation. Regional maxima is used to extract tumor region from the brain image.

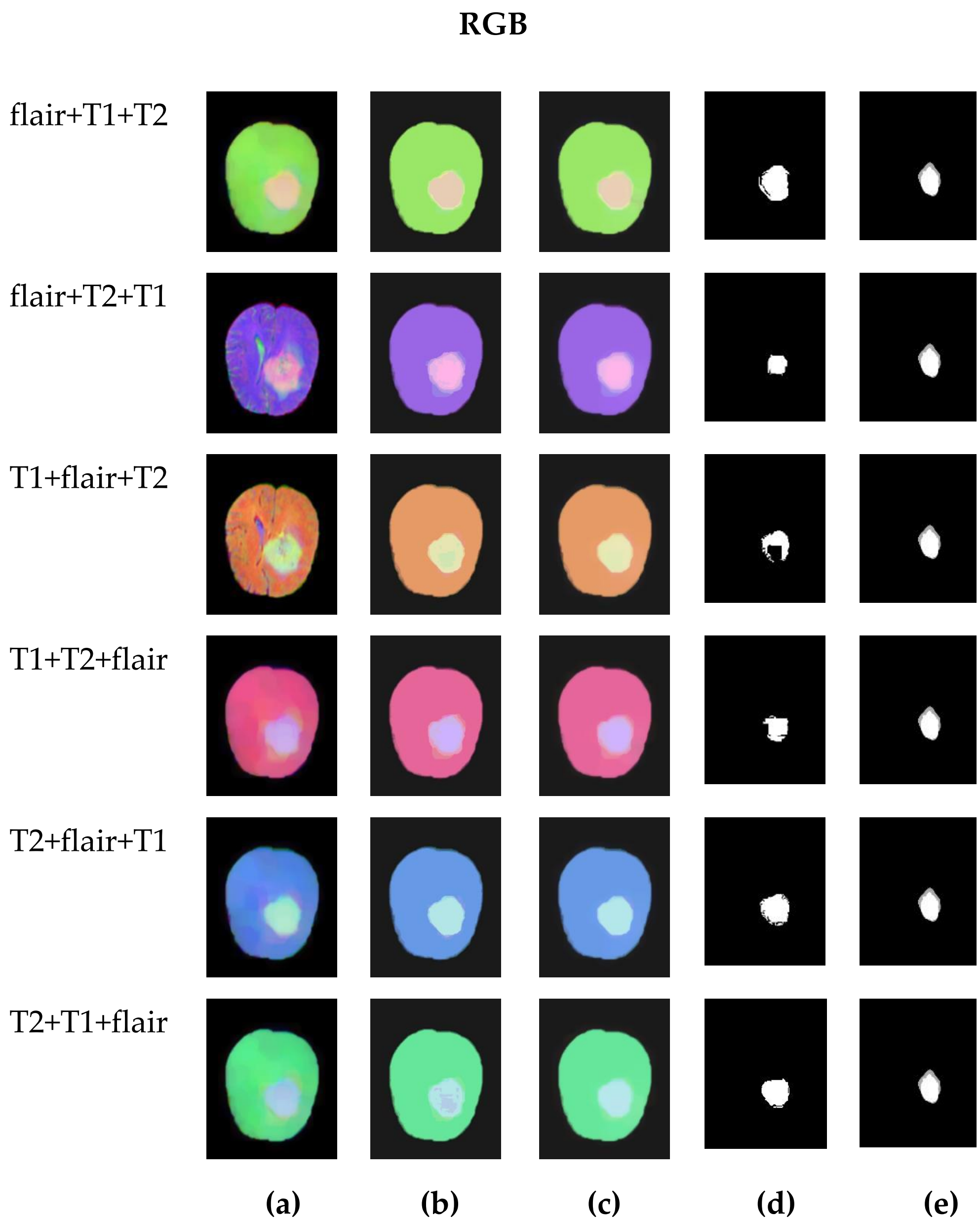


Fig-10: (a) Pre-Processing, (b) segmented, (c) Post-Processing, (d) Final result, (e) Ground tooth- of image1

L*a*b*

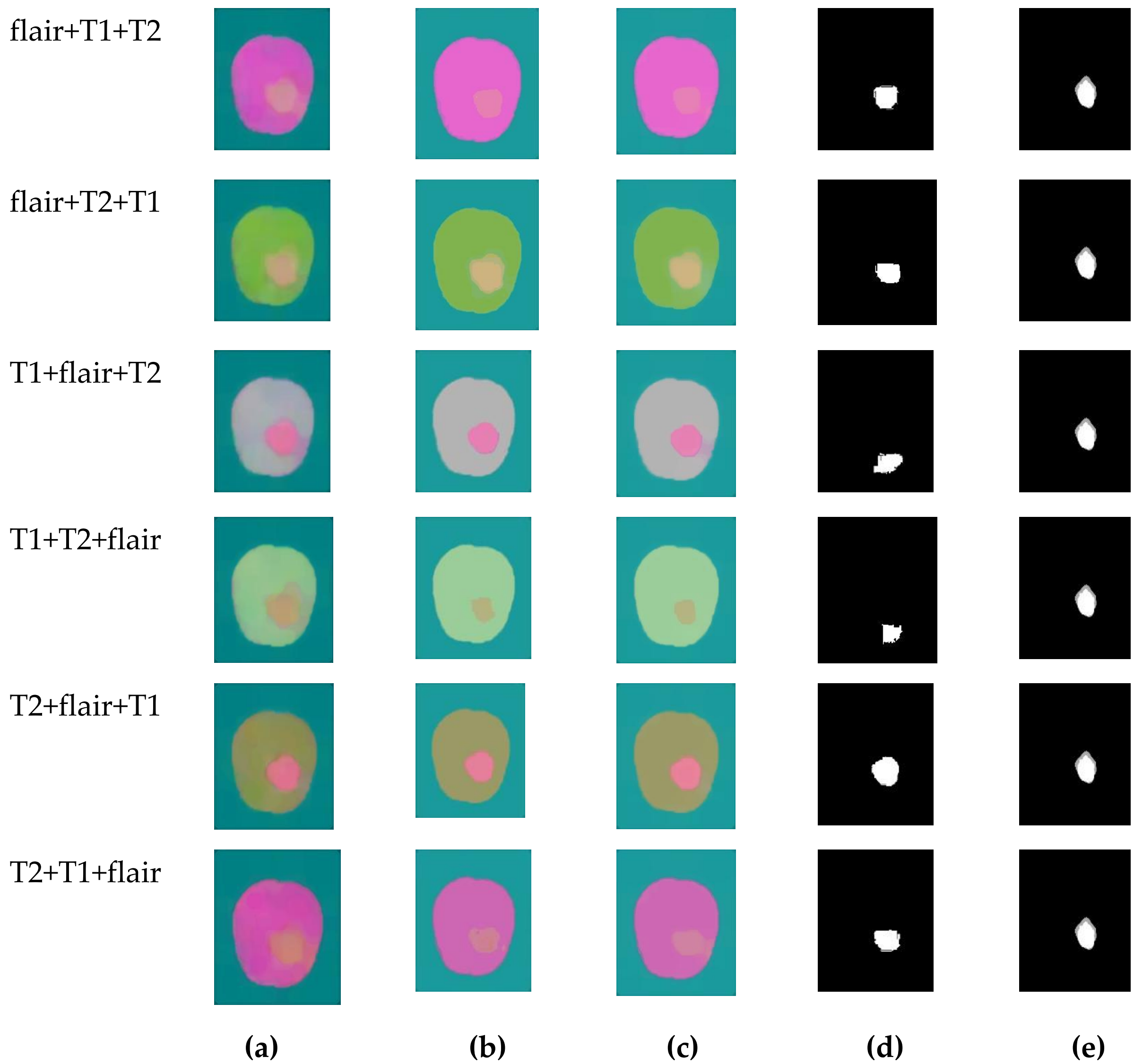


Fig-11: (a) Pre-Processing, (b) segmented, (c) Post-Processing, (d) Final result, (e) Ground tooth- of image1

YCbCr

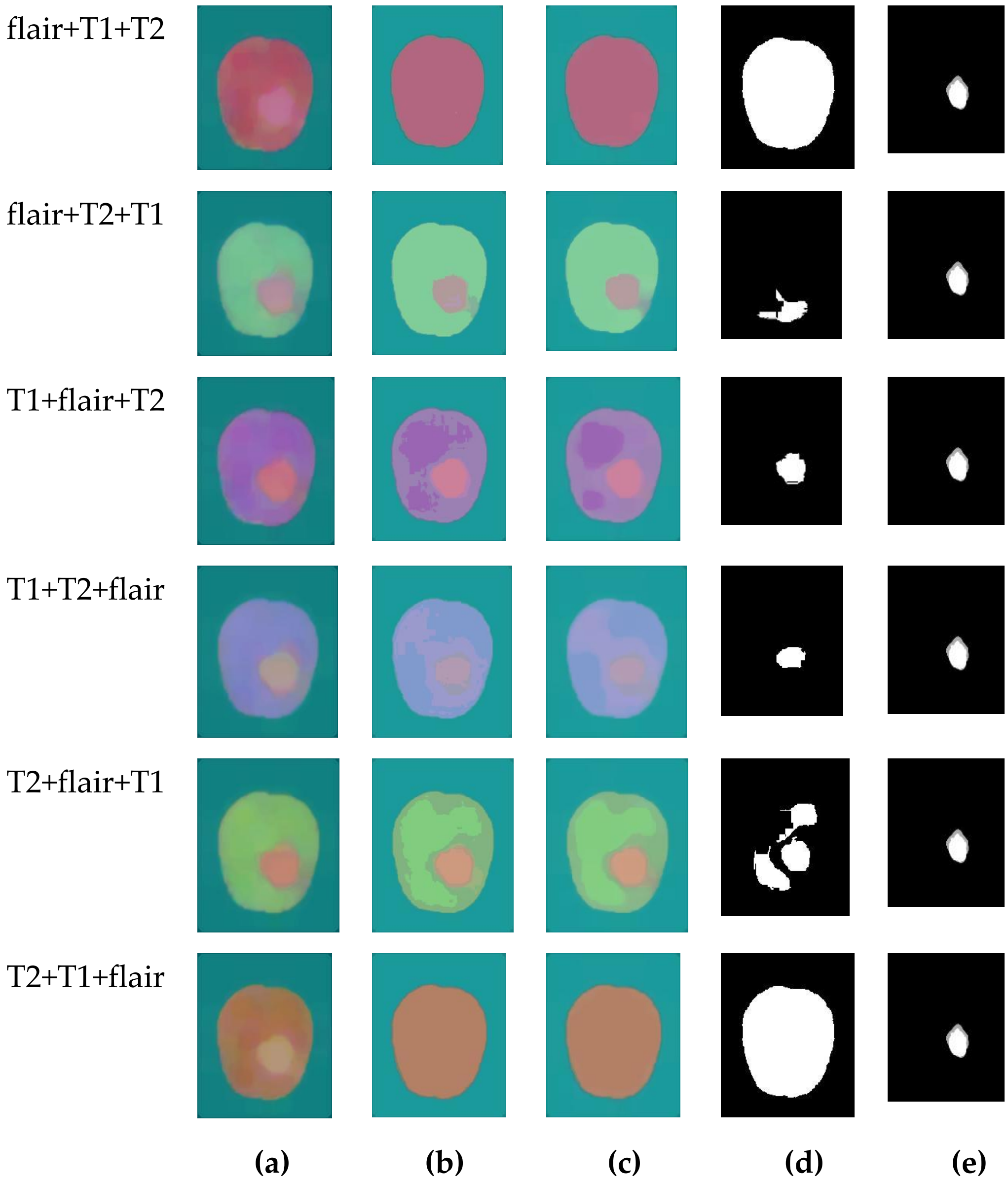


Fig-12: (a) Pre-Processing, (b) segmented, (c) Post-Processing, (d) Final result, (e) Ground tooth- of image1

5.2 Misclassification Error:

Finally calculate misclassification error for quantitative evaluation. We have taken 12 sample images i.e T1, T2 and flair and out of six combination we have to find out which combination gives lowest error which is shown in the following table

Table-1: Average value of misclassification error of six combination of 12 sample images

Combination	RGB	L*a*b*	YCbCr
flair+T1+T2	0.0908	0.0603	0.1467
flair+T2+T1	**0.0389**	0.0779	0.1283
T1+flair+T2	0.0595	0.0930	0.0608
T1+T2+flair	0.0664	0.1006	0.0431
T2+flair+T1	0.0482	0.0663	0.0852
T2+T1+flair	0.0876	0.0665	0.1116

According to this table-1 we observed that out of six combination flair+T2+T1 combination in RGB gives the lowest value of misclassification error. Therefore the flair+T2+T1 in RGB is the best combination.

5.3 Conclusion:

In this paper brain image is segmented using mean shift clustering because mean shift clustering does not require any prior knowledge regarding the shape of the image and number of cluster. It follows some Pre-Processing and Post- Processing techniques to reduce noise of image and finally using Regional Maxima the tumor region is extracted properly. According to the quantitative evaluation using MSE (Misclassification Error) out of six combination flair+T2+T1 combination in RGB gives the lowest value of misclassification error. Therefore the flair+T2+T1 in RGB is the best combination.

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