CHAPTER – 4

IMAGE PROCESSING AND IMAGE ANALYSIS

4.1 INTRODUCTION:

Digital Image Processing deals with manipulation and analysis of images by using computer algorithm so as to improve pictorial information for better understanding or clarity. This area is characterized by the need for extensive experimental work to establish the viability of proposed solutions to a given problem [27]. Image processing involves the manipulation of images to extract information to emphasize or de-emphasize certain aspects of the information contained in the image or to perform image analysis to extract hidden information. One of the factors contributing to the exponential growth of this field is declining cost of computer equipment and fast storage devices. Medical Image Analysis is one of the important applications which include analysis of digital mammograms, segmentation and classification of MR Images and many more. Even though final diagnosis of the disease depends solely on medical expert, various expert systems have been developed. Such systems combine expert knowledge with interactive image processing and act as supporting tool in the diagnosis process by providing precise information about presence of tumor [26,27].
Various medical imaging methods like MRI, MRA, X-ray CT, PET and SPECT provide a means for correlation of anatomy of organs with its functionality.

Recent advances in MRI system design have resulted in significant improvements in the areas of anatomical, functional and dynamic imaging procedures. MRI segmentation has been proposed for a number of clinical investigations of varying complexity [21]. In this context, MRI segmentation is becoming an increasingly important image analysis step for a number of application areas that include:
(i) Identifying anatomical areas of interest for planning of diagnosis, treatment, or surgery where the localization of the both normal tissues and tumor tissue needs to be accurately identified.
(ii) Preprocessing for multimodality image registration
(iii) Measurements of tumor volume and its response to therapy

The algorithms presented in this chapter are implemented in MATLAB 7.1 and are applied on MR Images. Basic image processing and analysis system and algorithms for filtering, edge detection and segmentation of brain tumor using various methods are described in the following sections.

4.2 BASIC IMAGE PROCESSING AND ANALYSIS SYSTEM

The Computer Vision System aims at recognizing objects of interest from given images and holds the possibility of developing the machine that can perform visual function parallel to human vision. Computer Vision System comprises of filtering, coding, enhancement, restoration, feature extraction, analysis and recognition of objects from image [27]. Processing of an image includes improvement in its appearance and effective representation of input image suitable for required application.

Thus, the process of image processing and image analysis initiates from acquiring visual information to giving out of its interpretation[28]. It comprises of following stages:
(i) Digitization and representation to convert visual information into a digitized form suitable for further processing
(ii) Preprocessing of image for improving its quality by filtering

(iii) Analysis of image by extracting image features and recognition or classification

A digital image is simply a matrix where each number represents the brightness at regularly spaced points or very small regions in the image. Mathematically, an image may be defined as a two dimensional function, \( f(x, y) \), where \( x \) and \( y \) are spatial (plane) coordinates and the amplitude of \( f \) at any pair of coordinates \( (x, y) \) is called the intensity or grey level of the image at that point.

Figure 4.1 shows the block diagram of Image analysis system. It performs preprocessing of input image which involves appropriate representation of input data, resizing and filtering, feature extraction, segmentation and classification.

![Fig.4.1 Image analysis system](image)

Preprocessing improves the quality of the data by reducing artifacts. Feature extraction and selection provides the measurement vectors using which the image segmentation is performed. Segmentation groups pixels into regions, and hence defines the boundaries of the tumor regions. Segmentation is followed by classification or labeling of the regions into the tissue types[29]. Classification is performed by estimating different features of the segmented region.

### 4.3 PREPROCESSING

The preprocessing of image aims at selectively removing the redundancy present in MR images without affecting the details that play a key role in the diagnostic process. The utility of segmented MR images in the medical diagnostic process depends on the combination of two factors. One is the elimination of the redundant information present in the original MR images and the preservation of
the important details in the resulting segmented images[21,37]. A proper representation of image is a prerequisite to an efficient processing technique such as enhancement, filtering, analysis and image communication.

In the presented study, the implemented algorithms are designed to operate on multi slice MRI scans of the human brain with tumor to extract the boundaries of tumor in each slice. The preprocessing of the MR images are performed as explained in the following steps.

4.3.1 Image acquisition

The technical equipment used for Standard T1, T2, and Proton Density images is 1.5 Tesla GE Sigma MRI Scanner. Images were selected from large series of axial images of head. The image slices were 5 mm thick with 2.5 mm inter-slice space. All T1 weighted images were acquired using a standard spin-echo (SE) sequence while T2 weighted and PD Images are acquired using a fast spin-echo (FSE) sequence. Figure 4.2 shows a typical slice of MR Image of brain having tumor. The acquired images from MRI Scanner are stored in JPEG format.

Fig.4.2 Typical MR Image of brain
4.3.2 Image resizing

The resizing of image is performed by the process of interpolation. It is a process which resamples the image to determine values between defined pixels[29]. Thus, the resized image contains more pixels than that of original image, the intensity values of additional pixels are obtained through interpolation. Various interpolation methods are,

(i) Nearest Neighbor Interpolation
(ii) Bilinear Interpolation
(iii) Bicubic Interpolation

All the interpolation methods work in a fundamentally similar way. In each case, to determine the value for the interpolation pixel, it finds a point in the input image that is corresponding to output pixel. It then assigns a value to the output pixel by computing a weighted average of some set of pixels in the vicinity of the point. The weights are based on the distance of each pixel from the output.

In this work, the resizing of the image is achieved by using the function \textit{imresize} in MATLAB environment. The function \textit{imresize} changes the size or sampling rate of an image using a specified interpolation method. If the method is not specified, the function determines the image type and automatically selects the best method. The function \textit{imresize} resizes an image by a factor or to specified row-column size. In the present study, all the algorithms are developed for their implementation on image size of 256 x 256 in JPEG format.

4.3.3 Filtering

Uncertainties are introduced into the MR image such as random image noise, partial volume effects and Intensity Non Uniformity artifact (INU), due to the inherent technical limitations of the MRI process. In Magnetic Resonance Imaging, inhomogeneity in the magnetic field gives rise to INU artifact[37]. This results in smooth and slowly varying change in image pixel values and lead to information loss, the SNR gain and degradation of edge and fine details.

Conventional linear low pass filtering of MR images is suggested in literature. Low pass filtering reduces noise relative to the true signal intensity in regions of the
image where the spatial features vary slowly [21]. Smoothing spatial filters are used for noise reduction. These filters are implemented by replacing the value of every pixel in an image by the average value of the gray levels in the neighborhood defined by the filter mask. Spatial neighborhood averaging is used as a linear operation on the input image given by equation,

\[ g(x, y) = \frac{1}{M} \sum_{s} f(m, n) \]  \[ (4.1) \]

where \( s \) is an \( M \)-pixel neighborhood of points, surrounding the point \((x, y)\).

However, implementation of linear low pass filter in this study showed that edges are not maintained. It means noise reduction is accomplished by blurring and has resulted in loss of fine details. The cost incurred in reducing noise and gaining contrast resolution is accompanied by loss of spatial resolution.

Problem of blurring edges during smoothing can partly be overcome by ordered statistic filter or weighted averaging method [27, 28, 29].

In weighted average method, pixels are multiplied by different coefficients, giving more importance (weight) to some pixels than others pixels i.e. pixel at the center of the mask is multiplied by a higher value than other. The other pixels are inversely weighted as a function of their distance from the center of the mask. The smooth gray level \( \bar{g}(r, c) \) is obtained by a linear combination of \( g(m, n) \) over a neighborhood where weights are dependent on their relative position within the neighborhood. Thus, the basic strategy behind weighing the centre point the highest and then reducing the value of the coefficients as a function of increasing distance from the origin is an attempt to reduce blurring in smoothing process.

Blurring of an image can also be avoided by using Order-statistics filters. These are nonlinear spatial filters whose response is based on ordering (ranking) the pixels contained in the image area encompassed by the filter and then replacing the value of the center pixel with the value determined by the ranking result. In the ordered static filter, the weights are dependent on the order of the sorted gray level over the neighborhood.

Suppose, \( x_i \) (\( i = 0, 1, 2… \Omega -1 \)) represent the gray level at the pixels in the neighborhood region, and \( x_{\{i\}} \) represent the same sorted in ascending. Therefore, \( x_{\{0\}} \)
is the minimum gray level while \( x_{\Omega + 1} \) is the maximum gray level in the neighborhood. The ordered statistic filter obtains the gray level at the pixel \( (r, c) \) of the smooth image by the relation.

\[
\bar{g}(r, c) = \sum_{i=0}^{\Omega-1} w_i x_{ij}
\]

Where \( w_i \) is the \( i \)th weight.

One of the most popular order statistic filters is the median filter. The median filter reduces the variance of the intensities in the image. Median filters change the image intensity mean value, if the spatial noise distribution in the image is not symmetrical within the window. These filters preserve certain edge shapes and location of edges and are very effective to remove impulsive noise.

If equation 4.1 is used to define the median filter, then we get,

\[
w_i = \begin{cases} 
1 & \text{if } i = \Omega - 1/2 \\
0 & \text{otherwise}
\end{cases}
\]  

(4.3)

Computation of median filter requires sorting of gray levels of pixels in filter window. For large window sizes, computation time is large. The algorithm used here is based on list sorting. Here, the median is calculated iteratively, by bit position, starting with MSB. After the median bit for a bit position is determined, only intensity values with this bit are retained for subsequent calculation. This procedure terminates, for \( n \) bit data, after \( n \) iterations, regardless of size of window [30].

Algorithm for the above concept is explained below:

(i) Input the gray values in binary representation.

(ii) Find the median value of all the most significant bits.

(iii) Find the median value of the next least significant bit.

(iv) Continue finding the median value of the next LSB bit, till all the bits are exhausted.

(v) Write the median bits, starting from that of MSB to LSB. This is the overall median value.
Thus, the principal function of median filter is to force points with distinct gray levels to be more like their neighbors. Figure 4.3(a) and Figure 4.4 (a) show raw original MR Image of brain with tumor. Median filtered image is displayed in Figure 4.3 (b) and Figure 4.4 (b).

4.4 EDGE DETECTION

In area of image processing and computer vision, edges or contours of images provide valuable information towards human image understanding. Edges are often
used in image analysis for finding region boundaries[28,56]. Edges are the representation of discontinuities of image features.

Edge is the boundary between two regions with relatively distinct gray level properties. In a continuous image, a sharp intensity transition between neighboring pixels is considered as an edge. Edge corresponds to fast change in gray level and thus, considered as high frequency information. Therefore, the process of separation of high frequency information is edge detection.

The process of edge detection is broadly classified into two categories, namely, Derivative approach and Pattern fitting approach.

Derivative operator or Gradient operator detects edge pixels by taking derivative followed by thresholding. Two dimensional derivative operators calculate derivatives by edge masks.

First order derivatives of a digital image are based on various approximations of the 2D gradient [27]. The gradient of an image \( f(x, y) \) at location \( (x, y) \) is defined as the gradient vector, given by the equation,

\[
\nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}
\]

This gradient vector points in the direction of maximum rate of change of \( f \) at coordinates \( (x, y) \). The magnitude of the gradient vector gives the maximum rate of change of \( f(x, y) \) per unit distance in the direction of \( f \).

The rate of change in gray level with respect to horizontal distance in a continuous image is equal to the partial derivatives as:

\[
\frac{\partial f(x, y)}{\partial x} = \lim_{\Delta x > 0} \frac{f(x + \Delta x, y) - f(x, y)}{\Delta x} \quad \ldots (4.5)
\]
For $\Delta x = 1$ (smallest possible non zero value of $\Delta x$ in a sampled image), then

$$f'_x(x, y) = f(x + 1, y) - f(x, y) \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (4.6)$$

where $f'_x$ represents the difference in $f$ with respect to $x$.

Similarly,

$$\frac{\partial f(x, y)}{\partial y} = \frac{f'_y(x, y)}{f(x + 1, y) - f(x, y)} \quad \ldots \ldots \ldots (4.7)$$

These finite differences represent the change in gray level from one pixel to the next and can be used to emphasize or detect abrupt change in gray level in the image. Since the edges of the objects in a scene often produce such high changes, these operators are called edge detectors[31]. The detected edge gives a bright spot at the edge and dark elsewhere. Convolution of the image with masks is used to calculate derivative or slope of an image in all directions. The idea is to take 3 x 3 section of the image. The products are added and the results are placed in the centre point of the image. These masks amplify the slope of the edge [28].

4.4.1 Edge detection using gradient operator

The one-dimensional edge detectors in equations (4.4) and (4.5) are represented by the operators.

$$\begin{bmatrix} -1 & 1 \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} 1 \\ -1 \end{bmatrix} \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (4.8)$$

The edge detector $g'_x(x, y)$ and $g'_y(x, y)$ indicate how fast the gray level is increasing or decreasing with distance in $x$ and $y$ directions. A positive value of $g'_x(x, y)$ indicates a transition from low gray level when moving to right whereas a negative value shows transition from high to low [32].
Many edge detectors are suggested in literature such as:
  a. Roberts Operator
  b. Prewitt Operator
  c. Sobel Operator
  d. Laplacian Operator

These masks or operators are compass gradient or directional edge detectors. This means that each one of the eight masks detects an edge in one direction. Given a pixel, there are eight directions that travel to a neighboring pixel. The directional edge detector detects an edge in only one of the eight directions. For the detection of all the edges, it is required to perform convolution over an eight times using each of the eight masks.

It is observed that Prewitt operator can detect vertical edges better than that of Sobel operator, while Sobel operator is superior to Prewitt operator in detecting diagonal edges. Roberts and 4 neighborhood operators are sensitive to noise. Effect of noise is reduced in case of Prewitt and Sobel operators by averaging of neighboring pixels[28,32]. Considering merits and demerits of various edge detectors, Sobel edge detector is implemented and shown below:

**Sobel Edge Detector**
Sobel edge detector combines uniform smoothing in one direction with edge detection [21,57] It is also defined by the operators that are factored:

\[
\begin{bmatrix}
-1 & 0 & 1 \\
-2 & 0 & 2 \\
-1 & 0 & 1
\end{bmatrix}
\times
\begin{bmatrix}
1 \\
2 \\
1
\end{bmatrix}
= 
\begin{bmatrix}
1 \\
-1 & 0 & 1 \\
1
\end{bmatrix}
\times
\begin{bmatrix}
1 \\
1 \\
-1 & 0 & 1
\end{bmatrix} = 
\begin{bmatrix}
1 \\
1
\end{bmatrix}
\]
So these operators are represented as number as number of shifts, additions and subtractions of the entire image. To accentuate the edges in the image (Fig 4.5), sobel horizontal and vertical edge detectors are applied, and the resulting of the two images are combined using the sum of absolute values to produce an edge magnitude image. The edges in the original image produce high gray levels (corresponding to white or light gray) in the edge.

![Fig. 4.5: Original MR Image](image1)

![Fig.4.6 Median Filtered Image](image2)

Figure 4.5 shows the original MR image, figure 4.6 shows the median filtered image. The edge detected brain tumor using sobel operator is shown in figure 4.7 (a).
4.4.2 Canny edge detector

This edge detector is based on first derivative combined with noise reduction and therefore, has become the most popular derivative operator for edge detection. The detection of step edges is influenced by the presence of noise. Therefore, the noise smoothing improves the accuracy of edge detection while adding uncertainty in localizing the edge [28,32]. Canny edge detector tries to achieve an optimal trade off between these two factors by approximating the first derivative of the Gaussian. Figure 4.7 (b) shows the output of Canny edge detection.

The results of Sobel and canny detector show that edge detected image includes tumor along with some normal brain tissues. This is due to overlapping gray level...
intensities same of tumor and normal tissues. Therefore, binary morphological dilation and erosion process are applied to detect edge of tumor.

### 4.4.3 Edge Detection using Morphological Operation:

In context to digital image processing, Morphology means study of topology or structure of objects from their image. In images, morphological operations are based on relations of two sets. One is an image and the second is a small probe, called a structuring element. The structuring element systematically traverses the image and its relation to the image in each position is stored in the output image[27].

Dilation and Erosion are fundamental morphological operations. Dilation expands an object to the closest pixels of the neighborhood. Normally, dilation is used to fill small holes and narrow gulfs in objects. If the original size needs to be preserved, then dilation is combined with erosion is explained in next subsection. Erosion shrinks the object. Erosion of an image is the operation of assigning to each pixel the minimum value found over a neighborhood of the corresponding pixel whereas dilation is the operation of assigning to each pixel the maximum value of the neighborhood. The structuring element is a function of two variables that specifies the desired local gray level property [33,36]. The value of the structuring element is added or subtracted for calculating maximum or minimum in the neighborhood.

Initially, binary erosion is used to eliminate all tissue types except tumor. Here, we have used the structuring element SE5. The Erosion operation is performed on threshoded image A. The eroded image B is obtain from the equation given below,

\[
B = (A \ominus SE5) \quad \ldots (4.7)
\]

where SE5 is a 3*3 square structuring element. Fig. 4.8 shows eroded image.

For performing dilation operation we have used structuring element SE9. Then the dilation operation is performed on eroded image B using the equation given below,

\[
C = (B \oplus SE9) \mid A \quad \ldots \ldots (4.8)
\]

where structuring element SE9 chosen for this step is square shaped with a diameter of three pixels. Dilated image is shown in figure 4.9.
This dilated image is then subtracted from the eroded image to get the edge detected image of tumor as shown in Figure 4.10.

Comparing the results of edge detection using Sobel operator, Canny edge detector and morphological edge detectors, it is observed that in case of Sobel and Canny operator detector, even normal brain tissues are detected along with tumor. The edge detection performed by morphological operation gives more precise edge detection of tumor and therefore further used in this study.
4.5 SEGMENTATION

Segmentation of an image is a process of dividing the image into homogenous, self consistent regions corresponding to different objects in the image. It separates image into meaningful regions[34]. Image can be segmented using basic properties of features of image like intensity, edge or texture.

Researchers in the area of medical image analysis have been trying to extract contours of different body organs and tissue types from medical images of various modalities. It is believed that objective evaluation of these medical image segmentation algorithms on a large set of clinical data is one of the important steps toward establishing validity and clinical applicability of an algorithm[35].

4.5.1 Problems encountered in Segmentation of MR Image

Accurate segmentation of brain tissues is important for both diagnosis and treatment strategies. The wide literature survey indicates that the accuracy of implementation of standard segmentation algorithms is hampered in MR images due to following reasons [21,35].

I. Lack of Standard: There is a compelling need for validation and comparison of medical image segmentation algorithms and standardized protocols. In medical image segmentation, the only standards available for comparison are segmentations produced by expert observers. Such segmentations cannot be considered as gold standards because they may suffer from observer bias and inter and intra observer variability. Such standards and statistical protocols are difficult to define for medical image segmentation because of the complex multidimensional nature of segmentation data and tedious and time-consuming data collection.

II. Optimal Selection of Features: The optimal selection of features in multispectral MRI is important to maximize tissue contrast differentiation, while minimizing the computational complexity. The level of operator supervision in the segmentation
process will impact the stability of the segmentation methods, due to inter- and intra-
observer variation.

III. MR Image Registration is another major problem in the classification of MR Images. Intensity variations are introduced by inhomogeneities in the radio frequency field and results in variations between slices in the same patient as well as between patient studies. In image segmentation, it is expected that the pixels in the same class should have similar pixel values independent of their locations. However, in magnetic resonance imaging (MRI), inhomogeneity in the magnetic field usually gives rises to the intensity nonuniformity (INU) artifact. This has adverse effect on the performance of intensity based automatic segmentation methods. Along with INU artifact, poor contrast and imaging noise reduces accuracy of segmentation.

4.5.2 Types of Segmentation

Depending on type of input image samples used for the proposed work, segmentation can be classified as mentioned below [21,34]:

I. Gray Scale Single Image Segmentation

II. Multispectral Segmentation

I. Gray Scale Single Image Segmentation:

In gray scale segmentation, a single image is used for feature extraction and segmentation. The gray scale single image segmentation methods can be subdivided as:

a. Edge based segmentation methods: Edge detection schemes suffer from incorrect detection of edges due to noise, over- and under-segmentation and variability in threshold selection in the edge image.

b. Region growing segmentation methods: The segmentations require an operator to select seeds and thresholds. Pixels around the seeds are examined and included in the region if they are within the thresholds. Results obtained with seed growing are generally dependent on the operator settings.

c. Threshold based segmentation methods: The most intuitive approach to segmentation is global threshold, which has been performed on various types of medical images. One common difficulty with this approach is determining the value of
the thresholds. Interactive (operator) selection of thresholds for the intra-cranial region has been reported. Gray scale segmentation methods are generally limited to relatively simple structures. For complex pathology, more information is required which is available in multispectral MRI data.

II. Multispectral Segmentation

Depending upon necessary operator intervention, Multispectral Segmentation is classified as mentioned below:

a. Unsupervised Segmentation
b. Supervised Segmentation.

a. Unsupervised segmentation
Unsupervised techniques, also called ‘clustering’, automatically find the structure in the data. A cluster is an area in feature space with a high density. Unsupervised methods are automatic, in the sense that operator intervention is necessary to complete the process, but the result should be operator independent. The input data consists of the features selected from the desired class of region. An unsupervised segmentation method defines regions in the image without operator input. However, these regions do not have an anatomical meaning associated with them. Therefore, a classification step is necessary to come to a labeled output image.

b. Supervised segmentation methods
Supervised methods require operator input for segmentation. This can be done by selecting training pixels or training regions on the images. Supervised methods include several pattern recognition techniques. Many pattern recognition methods are assuming particular distributions of the features and are called parametric methods. The means and covariance matrices for each of the tissues are estimated from a user supplied training set, usually found by drawing regions of interest (ROI) on the images. The remaining pixels are then classified by calculating the likelihood of each tissue class, and picking the tissue type with the highest probability. Parametric methods are only useful when the feature distributions for the different classes are well known; therefore this method is not applicable for MR image segmentation [70].
The difference between supervised and unsupervised methods is summarized in the figure 4.7:

Fig.4.11 Supervised and unsupervised image segmentation schemes
One of the supervised segmentation method recommended in literature is manual feature space segmentation method. In this type of segmentation, the threshold is selected manually by various method explained below.

4.5.2.1 Threshold based segmentation

Gray level thresholding is the simplest, computationally inexpensive and fast segmentation process. If the region of interest or objects has clearly distinct gray levels from background gray levels, then thresholding is a suitable segmentation method [28,32]. Correct threshold selection is crucial for successful threshold segmentation. This selection can be determined interactively or it can be result of some threshold detection method. In adaptive thresholding, the threshold value varies over the image as a function of local image characteristics.

Most complex methods of threshold detection are based on histogram shape analysis as explained below.

Histogram Based Segmentation:

Histogram based segmentation method uses the histogram to select the gray level for grouping pixels into regions [29, 34]. In an image, there are two entities: the background and the object, which can be differentiated by their gray level. The histogram of an image represents the gray levels of all the pixels of an image. Thresholding takes any pixel whose gray values are above threshold and sets all other to zero. The histogram peaks and the valleys between them are the keys for segmenting the image.

There are four segmentation techniques used for segmenting an image based on histogram and are described as below:

a. Manual Segmentation: In this method, the image and its histogram are inspected manually. Trial and error method is adopted to obtain better results. Even though manual thresholding gives better results, due to its trail and error methodology, it is time consuming and difficult to apply to large data set.

In case of most of the tumors, specifically, the most common type of tumor i.e. Glioblastoma Multiforme, brain tumor has the higher gray values than its surrounding tissues. Histogram of Glioblastoma Multiforme brain tumor, the largest peak of the
histogram represents the tumor. The threshold is set to a level above white matter. Figure 4.12 shows the median filtered MR Image and figure 4.13 shows its histogram.

![Fig. 4.12 Original MR Image](image1)

![Fig. 4.13 Histogram of MR Image](image2)

By observing the histogram of the MR Image the threshold value is set between 40 to 55 and then the segmentation is performed. The resultant segmented tumor is
shown in figure 4.14 (b). The filtered image is shown in figure 4.14(a). This segmented tumor tissue is now used for determining texture descriptors using various methods.

**Fig. 4.14(a) Filtered MR Image**  **Fig.4.14(b) Segmented Tumor**

b. **Histogram Peak Technique:** This method finds the two peaks in the histogram corresponding to the background and object of the image. It sets the threshold halfway between the two peaks. By reviewing the histogram precisely, the threshold has to be decided for optimum results of segmentation.

c. **Histogram Valley Technique:** This technique uses the peaks of the histogram, but concentrates on the valleys between them. Instead of setting the midpoint arbitrarily halfway between the two peaks, the valley technique searches to peaks to find the lowest valley.

**Fig.4.15 Filtered Image**
Figure 4.15 shows the original MR Image and figure 4.16 shows its histogram.

![Fig. 4.16 Histogram of MR Image](image)

The observation of the above histogram indicates a valley between two peaks at approximately 20 and 120. Therefore, by selecting the threshold between to peaks i.e threshold is set approximately near 75. The resultant segmented tumor is shown in figure 4.11.

![Fig 4.17 Segmented Brain Tumor](image)

c. Adaptive Histogram Technique: In this method, the peaks of the histogram are used in the first pass and adopt it to the objects found in the image in second pass. In the
first pass, the adaptive technique calculates the histogram for the entire image. This
smoothes the histogram and uses the peak technique to find the high and low threshold
values.

In the second pass, the technique works on each row and column area of the
image individually. In each area, it segments using the high and low values found
during the first pass. Then it computes the mean value for all the pixels segmented into
background and object. It uses these means as new peaks and estimates new high and
low threshold values for that rows x columns area Now, it segments that area again
using the new value.

### 4.5.2.2 Region growing segmentation

is based on the principle of identifying various
regions in an image that have similar features. It requires an operator to select seeds and
thresholds. Pixels around the seeds are examined and included in the region if they are
within the thresholds. Results obtained with seed growing are generally dependent on
the operator settings. Region based segmentation approach is less sensitive to noise than
boundary based approach[28,29] . This method is generally better in noisy images where
borders are difficult to detect. As quality of MR images suffers due to INU artifacts and
noise, region growing segmentation method is adopted in this study to segment tumor
as explained below:

Initially, a threshold is set that divides an image into two or more region. Then it
is essential to identify which pixels belong to each of these specific regions so as to
classify them in different classes. By setting one or more thresholds, the numbers of
gray levels in an image are reduced and that these gray levels are all nonnegative. Then
a region-labeling algorithm is used, that replaces each pixel by a negative number
representing the label of the region to which the pixel belongs. The algorithm uses a list
to keep track of pixels that are yet to be labeled. This list has two operations : (i )
insert \((s, t)\), which inserts the pixel \((s, t)\) at the end of the list and (ii ) \((s, t)\) remove \((\cdot)\),
which removes the pixel from the front of the list and saves it for further use as the
pixel \((s, t)\).

The algorithm begins by scanning the image from left to right, top to bottom.
When an unlabeled pixel \((x, y)\) is found, the algorithm will label all the pixels in the
4 – connected region to which \((x, y)\) belongs before it labels any pixels from other
regions. Initially, a new label $L$ is obtained. Then it labels $(x, y)$ as $L$ and adds $(x, y)$ to an initially empty list of pixels whose neighbors are to be checked later. Next, it removes the pixel $(s, t)$ least recently placed in the list (which initially will be the pixel $(x, y)$ just labeled). It next labels with ‘$L$’ each unlabeled 4-neighbor of $(s, t)$ that has the same gray level as $(s, t)$ and inserts each such 4-neighbor in the list (such 4-neighbor belongs to the same region as $(s, t)$). Then the process is repeated. If the list is not empty, it removes from the list the pixel $(s, t)$ least recently placed in the list. Again, it labels with $L$ each unlabeled 4-neighbor of $(s, t)$ that has the same gray level as $(s, t)$ and inserts each such 4-neighbor in the list. Whenever the list is empty, one entire region has been labeled, at which point this process is terminated and resumes scanning the image from left to right, top to bottom, looking for another unlabeled pixel. If such a pixel is found, it obtains a new label and restarts the labeling process.

The pseudo code for the region-labeling algorithm is as given below; in which, $g(x, y)$ represents the gray level of the pixel $(x, y)$. As the algorithm executes $g(x, y)$ is changed to the label of pixel $(x, y)$. Undefined gray levels outside the image such as $g(x, -1)$ and $g(-1, y)$ are considered to be unequal to any gray level in the image. The labels are negative numbers -1, -2, ……

**Pseudo code for Region – Labeling Algorithm**

$L$ $\leftarrow$ -1 (Initialize label.)

Scan the image from left to right and top to bottom for all $(x, y)$

If $g(x, y) \geq 0$ then insert $(x, y)$

while list is not empty do

$(s, t)$ $\leftarrow$ remove ( )

For each 4-neighbor $(u, v)$ of $(s, t)$ do

If $(u, v)$ is unlabeled and $g(u, v) = g(x, y)$ then

insert $(u, v)$

end if

end for

end while

$L$ $\leftarrow$ $L$ - 1 (Get new label)
Figure 4.18 shows the filtered MR image and figure 4.19 shows the segmented tumor using region growing algorithm.

![Fig. 4.18 Original MR Image](image1) ![Fig 4.19 Segmented Brain Tumor](image2)

Comparison of results of various segmentation techniques highlights following points:

(i) In case of Supervised threshold based segmentation, selection of optimum threshold is critical. Overlapping intensities of tissues of different class makes the selection of threshold critical.

(ii) Edge based segmentation suffers from incorrect detection of edges due to nonuniform nature of MR Images. A global threshold can not give satisfactory segmentation results and therefore additional features are required.

(iii) Canny edge detector improves the segmentation performance as it is based on first derivative approach combined with noise reduction.

(iv) By applying morphological operations like dilation and erosion, edge detection performance can be improved.

(v) Performance of Region growing algorithm is dependent on operator settings. The optimum results are obtained only for well defined regions.
SUMMARY

Digital Image Processing deals with manipulation and analysis of images by using computer algorithm so as to improve pictorial information for better understanding or clarity. Medical Image Analysis is one of the important applications which include analysis of digital mammograms, segmentation and classification of MR Images etc.

Image analysis system explained in the presented work comprises of preprocessing, segmentation, feature extraction and classification. Preprocessing improves the quality of the data by reducing artifacts. Feature extraction and selection provides the measurement vectors using which the image segmentation is performed. Segmentation groups pixels into regions, and hence defines the boundaries of the tumor regions. Segmentation is followed by classification or labeling of the regions into the tissue types. Classification is performed by estimating different features of the segmented region.

The preprocessing of the MR images is performed by image acquisition, image resizing and filtering. Smoothing operation is used primarily to diminish the effects of INU artifacts, noise due to motion and shift. Problem of blurring the edges during smoothing can partly overcome by ordered statistic filter. One of the popular ordered statistic filters is the median filter.

The most common approach in detecting meaningful discontinuities in gray level is edge detection. Derivative operator or Gradient operator detects edge pixels by taking derivative followed by thresholding two dimensional derivative operators calculate derivatives by edge masks.

Sobel, Canny edge detectors are implemented in this study. To overcome the drawbacks of this detector, the edge detection is performed using morphological operations like dilation and erosion.

Segmentation of an image is a process of dividing the image into homogenous, self consistent regions corresponding to different objects in the image. Accurate segmentation of brain tissues is important for both diagnosis and treatment strategies. Accuracy of implementation of standard segmentation algorithms is hampered in MR
images due to lack of standard, Optimal Selection of Features and artifacts due to MR Image Registration.

Depending on type of input image samples used for the proposed work, segmentation can be classified as Gray Scale Single Image Segmentation and Multispectral Segmentation. Depending upon necessary operator intervention, Multispectral Segmentation is classified as Unsupervised Segmentation and Supervised Segmentation.

Histogram based supervised manual segmentation method, region growing segmentation and edge based segmentation methods are implemented used in this study.

Comparison of results of various segmentation techniques highlights following points:

(vi) In case of Supervised threshold based segmentation, selection of optimum threshold is critical. Overlapping intensities of tissues of different class makes the selection of threshold critical.

(vii) Edge based segmentation suffers from incorrect detection of edges due to nonuniform nature of MR Images. A global threshold can not give satisfactory segmentation results and therefore additional features are required.

(viii) Canny edge detector improves the segmentation performance as it is based on first derivative approach combined with noise reduction.

(ix) By applying morphological operations like dilation and erosion, edge detection performance can be improved.

(x) Performance of Region growing algorithm is dependent on operator settings. The optimum results are obtained only for well defined regions.