# BRAIN TUMOR SEGMENTATION USING OPTIMIZED HYBRID CLUSTERING TECHNIQUE BASED ON DYNAMIC HISTOGRAM EQUALIZATION

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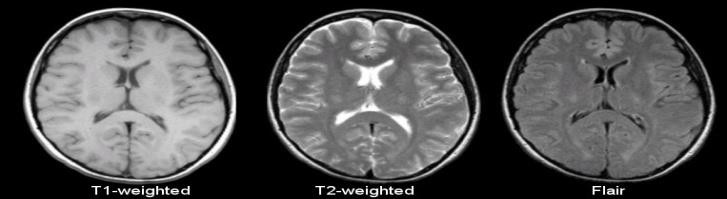
**Abstract:**

***Image segmentation is the most challenging task in the field of medical image processing. Medical image segmentation is the most essential and crucial process in order to facilitate the characterization and visualization of the structure of interest in medical images. Segmentation of brain tumor plays an important role in medical image analysis. Impact of tumor from MRI brain image data remains an onerous task because of complex structure of brain tumors. To palliate the image artifacts such as noise, intensity inhomogeneity, and improve the segmentation accuracy, a fruitful hybrid clustering approach is proposed. This paper presents an efficient image segmentation approach using an optimized hybrid clustering approach based on advanced morphological operations and dynamic histogram equalization. Results have been achieved using evaluation parameters like F score, precision, accuracy, specificity, and recall.***

***Keywords: K Means, Fuzzy C Means, Bias Corrected Fuzzy C Means, Machine Learning.***

1. **Introduction:** One of the most promising areas of health innovation is the application of AI in medical imaging, including, but not limited to, image processing and interpretation. According to recent research more than 50% of global healthcare leaders expect an expanding role of AI in monitoring and diagnosis. The use of AI is already common practice in segmentation of images; researchers foresee a veritable boom in innovative AI applications over the next five to ten years. Numerous studies confirm the basic clinical value of this second generation of artificial intelligence in general. With the rapid development of computer and internet-plus technologies, digital medical treatment or diagnose has become a very popular and important means in modern science society, such as MRI, X-ray, CT, and PET [1]. Medical image processing deals with the problem scientific approaches to the enhancement of raw medical image data for the purposes of selective visualization as well as further analysis. Digital medical image processing has made a great impact in recent years. Medical image processing has made lots of achievements in the past decades. Due to various restrictions imposed by image acquisitions, pathology, and biological variation, the medical images are of high complexity and ambiguity as well as rich in noise and low in contrast [1]. The main objective of medical image segmentation is to extract the meaningful information from the medical image. It involves processing of an image into

different meaningful regions and extracts the most significant information by using analytic tools. The segmented images are further used for quantitative analysis and diagnose, such as disease or not. Using this meaningful information, the accuracy of operative treatment can be enhanced as well as provide accurate clues for size, location, shape and characteristics. We can roughly classify the existing techniques into five categories: edge detection methods, threshold based methods, clustering methods, boundary-based methods, and hybrid methods. Brain tumor is basically an abandoned growth of cancerous cells inside the brain or around the brain. According to WHO, tumor and stroke are the second and third leading causes of death after heart disease. In India, every year 40,000-50,000 persons are diagnosed with a brain tumor; out of these, 20% are children. WHO states that brain tumors are graded from I to IV, corresponding to least advanced to the most advanced diseases, respectively [5]. Among medical imaging modalities, MRI is one of the safest methods for processing data with high spatial resolution, and it is also a low-risk, non-invasive modality in comparison to other diagnostic imaging techniques. Due to this reason, the majority of research in medical image segmentation pertains to its use for MR images, and there are many methods available for medical image segmentation. Primary brain tumors do not spread to other locations and can be malignant or benign. Secondary brain tumors are always malignant. Both categories are life-threatening. Meningioma’s and gliomas are the examples of low-grade tumors, classified as benign tumors. The glioblastoma and astrocytomas are the examples of high-grade tumors, classified as benign tumors. Due to intense inhomogeneity, the detection of primary and secondary tumors is difficult. The diagnosis of brain tumor segmentation is composed of basic medical image processing techniques such as preprocessing, image segmentation, feature extraction and classification. The segmentation of gliomas is a challenging task because i) gliomas invade the neighboring tissue rather than displacing it which causes blurry and unclear borders. ii) gliomas may appear in, any position of brain tissue with varied size, shape, and appearance. iii) Intensity inhomogeneity. iv) Blood vessels appear bright; in contrast, the tumor parts which are necrotic do not have higher levels of intensity [3]. So, it is usually impossible to segment the tumor by thresholding the intensities in this imaging modality.

 Figure 1.1 Different modalities of MRI

|  |  |  |  |
| --- | --- | --- | --- |
| Tissue | T1 | T2 | FLAIR |
| CSF  White Matter Cortex  Fat Inflammation  Repetition time (TR) Echo time (TE) | Dark Light Gray Bright Dark 500  14 | Bright Dark gray Light gray Light Bright 4000  90 | Dark Dark gray Light gray Light Bright 9000  114 |

Table 1.1 MRI sequences and their approximate TR and TE time

Images obtained by MRI are utilized for analyzing and studying the behavior of the brain. Research shows that MR imaging gives more precise results for the discovery of metastases in comparison with other modalities. The most common MRI sequences are T1-weighted images and T2-weighted images. T1-weighted images are produced by using short TE (Time to Echo) and RT (Repetition Time) times. The contrast and brightness of the images are predominantly determined by T1 properties of tissue. Conversely, T2-weighted MR images are produced by using longer TE and RT times. In this, the contrast and brightness are predominantly determined by the T2 properties of tissue. Flair is the third commonly used MRI sequence.

# Literature Survey:

Parveen and Amritpal Singh [4] proposed a hybrid technique to detect brain tumor using Support Vector Machine (SVM) and Fuzzy C-Means Clustering (FCM). A real dataset of 120 patients’ MRI images experimented. The MRI images were converted to two-dimensional matrices (using MATLAB) for image enhancement. The segmented images are feature extracted by Gray Level Run Length Matrix (GLRLM) for better understating. Further, training the SVM classifier on 96 brain images, the remaining 24 brain images were used for testing to identify the tumor present in brain images. The tabulated performance of SVM Classifier revealed that the accuracy of linear Kernel function is about 91.66%. However, the author concluded that hybrid SVM algorithm might be implemented to improve the accuracy rate by reducing the error rate.

Anant and Siddu [6] proposed a method to classify medical images without human inspection. The proposed technique used Principal Component Analysis (PCA) to extract the features and applied Adaptive Neuro-Fuzzy Inference System (ANFIS) tool for training. The ANFIS classifier detected the tumors with the accuracy of 90%. The statistical results showed that ANFIS method outperformed PNN method by more than 90% for the same set of data. However, there is no clarity on the dataset used to evaluate the proposed method.

Santhoshkrishnan, Sivanarulselvan, and Betty’s study [7] concentrated on brain tumor detection and classification through image processing techniques. The tumor images from MRI and CT scans are used for the survey. The images from scan center are preprocessed initially for noise removal, and by Gray Level Co-occurrence Matrix (GLCM) method, the features are extracted. Further, an integrated approach of both Artificial Neural Network (ANN) and Fuzzy C-Means Segmentation technique was used for segmenting the tumor area from the original image; thereby, the limitations in both the methods were eliminated. Finally, ANFIS method classifies as either normal or abnormal image. In the case of abnormality, the type of defect was also specified. The technique was evaluated based on accuracy, specificity, and sensitivity. The results revealed that the proposed method is superior to the existing one, but the comparison or its values were not mentioned.

Mariam and Zaid’s work [8] concentrated on fully automated brain tumor detection on brain tumor images. The proposed image processing involves four steps for tumor detection

namely; (1) Pre-processing by Anisotropic diffusion filter for denoising MRI images, (2) The denoised images are masked based on symmetry, (3) SVM classifier detects the brain tumor from the masked images, and (4) The segmentation process was evaluated based on Dice- coefficient (DC) where a DC > 0.7 is ideal segmentation. When this algorithm was evaluated with 40 MRI brain images, brain tumor detection accuracy was found to be 95.5%. However, authors failed to specify the performance of the algorithm with standard dataset.

R.J.Ramteke et.al [9] proposed an automatic medical image classification technique. KNN classifier is used to classify the medical image into normal and abnormal image. KNN is the simple method which required low computational cost.

Priyanka, Balwinder singh [10] focused on survey of well-known brain tumor detection algorithms that have been proposed so far to detect the location of the tumor. The main concentration is on those techniques which use image segmentation to detect brain tumor. They proposed edge-based segmentation. The next step is stratified k-fold cross validation to avoid over fitting. The classification part was done using SVM. An intelligent classification rate of 96.65% was achieved.

Amitava Halder et.al [11] proposed brain tumor detection using segmentation-based object labeling algorithm. They proposed k means algorithm followed by object labeling algorithm. It is observed that the experimental results of the proposed method gave better results but time consuming.

Khushboo Singh, SatyaVerma [12] proposed advanced classification techniques based on Support Vector Machines (SVM) are proposed and applied to brain image classification using features derived. SVM is an artificial neural network technique used for supervised learning of classification. Important characteristics of SVM are its ability to solve classification problems by means of convex quadratic programming (QP) and also the sparseness resulting from this QP problem. The learning is based on the principle of structural risk maximization. Instead of minimizing an objective function based on the training samples (such as mean square error), the SVM attempts to minimize the bound on the generalization error (i.e., the error made by the learning machine on the test data not used during training).

|  |  |  |  |
| --- | --- | --- | --- |
| **Technique** | **Algorithm** | **pros** | **Cons** |
| **Filtering based Segmentation** | Sobel method with image dependent thresholding | Less false edges and have closed contours results in more accuracy than Sobel method | Limitations in tumor region area and thickness of boundary lines of region are more. |
| **Threshold based Segmentation** | Adaptive threshold approach and canny edge detection | Classify benign as well as malignant tumor | Fix the threshold value. Cannot be used for images with poor contrast or images with a lot of background and foreground artifacts. |
| **Clustering based segmentation** | K means | Simple and faster | Difficult to predict k value |
| **Segmentation based** | K means , region growing | Morphological operators is more accurate than k-means | Compared to Region growing method Morphological operators are semiautomatic Providing less accuracy. |
| **Segmentation** | GMM | Good for non-temporal pattern recognition | Require knowledge for the no of clusters |
| **Segmentation** | Genetic algorithm Combination of WST & WCT | More accuracy | This method is applied only to CT images |
| **Modular Approach To MRI Segmentation** | Symmetry analysis. | The proposed approach can be able to find the status of increase in the disease using quantitative analysis | Time consuming |
| **Clustering based segmentation** | K means clustering and BPN classifier | It combines clustering and Classification algorithm  Accuracy can be improved in less Time. | Initial K value |

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | | |
| **Segmentation based** | Expectation maximization | encode both spatial and statistical properties of the image | Require threshold Less % accuracy |
| **Segmentation based** | One class SVM | Achieved better results for tumor than fuzzy clustering | Optimization problem |
| **Skull Stripping** | Histogram Partitioning with Maximum Entropy Divergence. | Provide accurate segmentation of brain tissue by removal of non- brain tissues | Extraction of tumor only considers entropy parameter |

Table 2.1 summary of existing methods based on segmentation

# Segmentation techniques in MRI brain tumor analysis:

Segmentation is a method of dividing an MR image into multiple segments. The aim of segmentation is to change the representation of an image into meaningful information which is easier to analyze. Segmentation in medical images is a method of dividing the pixels in order to detect and separate the target area usually a lesion region from the background and healthy tissues [13]. In case of brain tumors, it is a challenging task because of the characteristics of tumor in the MR images. Several techniques for MRI segmentation have been developed over the years based on the tissue properties. These techniques can be dividing into five major classes: intensity-based techniques, manual segmentation, atlas-based methods, surface-based methods, and hybrid segmentation methods [14]. Fig 3 summarizes the various segmentation techniques. In fact, hybrid techniques and Soft computing techniques have established wide range applications in image segmentation. Also, deep learning techniques are widely applied to image segmentation.



MRI BRAIN IMAGE SEGMNETATION METHODS

* CASCADED CNN
* FCN&DCNN
* THRESHOLD BASED
* REGION BASED
* CLUSTERING BASED
* CLASSIFICATION BASED
* EM & ACTIVE CONTOURS
* HMRF & EM
* FCM&LVQ
* LEVEL SET&ANN
* SOM&FCM
* ITK-SNAP
* ATLAS BASED METHOD
* ATLAS-BASED FUZZY CONNECTIONS

DEEP LEARNING

HYBRID

ATLAS

INTENSITY

MANUAL

Figure 3.1various image segmentation techniques

# Segmentation Based on Clustering:

Over past decades, there have been many algorithms implemented for medical image segmentation. Clustering methods are the most widely used in pixel-based approaches for image segmentation, clustering is a process of grouping a set of points (feature vectors) into subsets (called clusters) so that points in the same cluster are similar to each other whereas in different cluster are dissimilar [15]. Several types of clustering methods are available for segmentation like K means, Fuzzy C-Means, and Expectation Maximization. Clustering techniques aim at minimizing an objective function according to some criteria. K means algorithm is a hard clustering algorithm, which iteratively calculates the gray scale means of different clusters, computes the distance from the image pixels to the cluster centroids, and assigns the image pixels to classes that corresponds to the nearest centroid.Fuzzy C-Means clustering utilizes the fuzzy set theory, which allows soft computation. The EM algorithm assumes that data can be described as a mixture of probability distributions. Then, the algorithm iteratively calculates the posterior probability and estimates the mean, covariance, and mixture, coefficients using the maximal likelihood estimation approach and clustering criteria. However this algorithm is sensitive to noise [2].





Preprocessing

Noise Reduction, Bias field and Intensity Inhomogeneity correction

Figure 3.2 Typical methodology of brain tumor analysis



Classification

Prediction of Tissue labels (HGG, LGG and no-tumor or Grade I, II, III, and IV)

Performance Evaluation

FeatureExtraction Texture, Intensity, shape

Segmentation

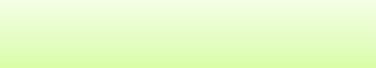
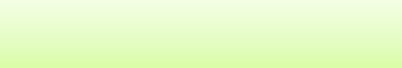
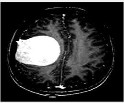
Separating the different tumor tissues

Interpretation and formulation of Diagnosis

# Segmentation based on hybrid clustering approach:

Why hybrid clustering is used in medical image segmentation? To find the proper choice of the segmentation algorithm for the given application is a difficult task in medical image segmentation. So, a novel approach is introduced which combines any two segmentation methods to improve the accuracy of segmentation [16]. The process of combining two segmentation methods is called as hybrid segmentation. This hybrid approach is used to find the exact lesion from MRI brain images. The main objective of combining the various algorithms is to remove the drawbacks of two difficult methods and to improve the accuracy of segmentation. Many researchers proposed a new method of hybrid algorithm for segmentation. Based on the extensive literature review, it is identified that the hybrid clustering is the most suitable method for segmentation [16]. Xiango.et.al (2002) proposed to overcome the disadvantages of the two methods by combining two different algorithms is called hybrid segmentation [17]. The proposed system utilized the combination of two algorithms in order to obtain the unique features of the two methods.

# The Proposed Medical Image Segmentation Technique:



Noisy MRI image

Histogram equalized image

Denoised image

Denoising (Gaussian filter, median filter)

Contrast enhancement Histogram equalization

Thresholded image

Advanced morphological operation (bi-level thresholding)

1. Clustering

KM

FCM

Clustering image

Segmentation

2. Modified FCM

BCFCM

3. Hybrid Clustering

MKIFCM

MARKFCM

Tumor extraction

Ground truth images

Segmented output

Repair tumor area Morphological operations

Tumor identification

Post processing

Performance evaluation

Figure 4.1 proposed block diagram of brain tumor segmentation based on optimized clustering approach

This study proposes a novel approach in order to achieve a precise segmentation using an optimized hybrid clustering technique based on dynamic histogram equalization and advanced morphological operations. The proposed method is implemented by using MATLAB of version 19a. It is installed on the operating system of Windows 10 with the Intel Rcore(TM) i7-4500U CPU 2.40 GHz and 16.0 GB of memory (RAM). The proposed medical image segmentation system consists of four stages: preprocessing, clustering, tumor extraction, contouring, and validation stages. The following stages explain the proposed methods by this study.

* 1. ***Preprocessing stage****:* Medical images are often noisy, which greatly affects segmentation of lesions and diagnosis of patient’s conditions. This phase consists of denoising the images based on advanced morphological operations [18]. This phase consists of three sub stages namely

1. *histogram equalization ii) denoising iii) Threshold based Stage 1: Histogram Equalization*

Image Enhancement methods: Enhancement procedures are divided into two classes specifically.

* 1. Spatial domain methods
  2. Transform domain methods

*Spatial domain methods: i) Histogram equalization*

It is a spatial domain method that produces output image with uniform distribution of pixel intensity means that the histogram of the output image is flattened and extended systematically. PDF and CDF are acquired via the input image histogram. These functions are applied to replace the input image gray levels to the new gray levels. Then, the processed image and histogram for the resultant image is generated.

1. *Dynamic histogram equalization*

This technique had overcome the drawbacks of histogram equalization. It shown a better brightness preserving and contrast enhancement than HE. The following figure explains the dynamic histogram equalization.



On each partition of histogram HE is applied

Assign specific gray levels to each portion of the histogram

Based on the local minima image histogram is divided

Find the local minima in the histogram

Get the histogram of the image

Input image

Figure 4.2 above flowchart explains the dynamic histogram equalization process

The following table gives the PSNR values of various histogram equalization techniques. The following graph shows the performance analysis of HE techniques. The following figure 4.3 shows better performance of the dynamic histogram equalization technique when compared with other methods.

|  |  |  |  |
| --- | --- | --- | --- |
| **MRI images** | **HE** | **DHE** | **AHE** |
| **Image 1** | 13 | 21 | 14 |
| **Image 2** | 11 | 22 | 22 |
| **Image 3** | 9 | 16 | 13 |

Table 4.1 PSNR values of various histogram equalization techniques

30

20

10

HE

DHE AHE

0

IMAGE 1

IMAGE 2

IMAGE 3

*Stage 2: Denoising*

Figure 4.3 PSNR graph for various Histogram Equalization techniques

1. *Gaussian Filter*: MRI images are usually corrupted by disturbances like Gaussian and poison noise. The vast majority of the denoising algorithms assume additive white Gaussian noise. Some algorithms that designed for Gaussian noise elimination such as edge preserving, bilateral filter, total variation, and non–local means [18]. In this paper, Gaussian filter is used to remove the noise. Gaussian filtering is used to blur images and remove noise, in one dimension, the Gaussian function is

𝐺(𝑥) = 1

√2𝜋 𝜎

−𝑥2

𝑒2𝜎2

(4.1)

where 𝜎 is the standard deviation of the distribution. The distribution is assumed to have a mean of 0. While working with images, there is need to use the 2D Gaussian function.

−(𝑥2+𝑦2)

1 𝑒

𝐺(𝑥, 𝑦) = 2𝜋𝜎2

2𝜎2

(4.2)

where 𝑥is the distance from the origin in the horizontal axis, 𝑦is the distance from the origin in the vertical axis, and 𝜎is thestandard deviation of the Gaussian distribution. The output of this sub step is the free noising MRI image.

1. *Sliding window spatial filter-Median filter:* It is originally known as order statistics filter. It is well known and usually used nonlinear filter [24]. This filter is used to remove the noises by smoothing the images. It also lowers the intensity variation between one and rest of all the pixels

of an image. It works by moving pixel by pixel through the image, replacing each value with the median value of neighboring pixels. The pattern of neighbors is called “window”, which slides pixel by pixel over the entire image. The median is calculated by first sorting all the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle (median) pixel order. Image processing researchers assert that the median filtering is better than the linear filtering for removing noise in the presence of edges. The output of this sub step is the free noising MRI image.

|  |  |
| --- | --- |
| 4.4 a. | 4.4 b. |

Figure 4.4 The effect of adding noise a) Gaussian filter output b) median filter output

|  |  |  |  |
| --- | --- | --- | --- |
|  |  |  |  |
|  |  |  |  |
|  |  |  |  |

|  |  |  |  |
| --- | --- | --- | --- |
| Type of Noise Gaussian Median noise metrics filter filter  Gaussian PSNR 23.725 25.497  noise  MSE 643.83 407.65  Poisson PSNR 30.085 29.212  noise  MSE 482.95 237.58 |  | | |
|  | 700  600  500  400 GAUSSIAN  FILTER  300  MEDIAN  200 FILTER  100  0  PSNR MSE |  |

Table 4.2 PSNR and MSE values of Gaussian and median filter by adding Gaussian and Poisson noise.

Figure 4.5 processing time of Gaussian filter and Median filter

From table 4.2 it is evident that median filter shows better performance for Gaussian and Poisson noise.

*Stage 3 Threshold based*

The noise removed image can be taken for thresholding process. Thresholding is an effective way of partitioning an image into a foreground and background. This image analyses technique is a type of image segmentation that isolates objects by converting grayscale image into binary image. Image thresholding [24] is most effective in images with level of contrast images. The thresholding operation is done based on the equation (4.3)

𝑖𝑓 𝐴(𝑥, 𝑦) ≥ 𝜃 𝐴(𝑚, 𝑛) = 𝑜𝑏𝑗𝑒𝑐𝑡 = 1; 𝑒𝑙𝑠𝑒 𝐴(𝑚, 𝑛) = 𝑏𝑎𝑐𝑘𝑔𝑟𝑜𝑢𝑛𝑑 = 0; (4.3)

𝜃 parameter is called bright threshold is chosen and applied to an image A(x,y).

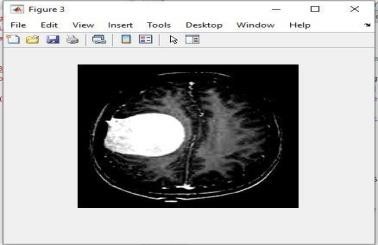


Figure 4.6 threshold based image

## Clustering stage

By de-noising the MRI image and removing skulls, the images are fed to the clustering stage. The preprocessing image is based on advanced morphological operations and dynamic histogram equalization. These preprocessed images are fed to the clustering stage [13]. This stage includes two clustering algorithms, one FCM based on intensity inhomogeneity correction and two hybrid clustering algorithms. i) K means ii) Fuzzy C means iii) Bias corrected FCM iv) MARKFCM

v) MKFCM.

1. **K means clustering:** It is a partitioning method which finds mutual exclusive clusters of spherical shape. It generates a specific number of disjoint, flat (non-hierarchical) clusters. Statistical methods can be used to cluster to assign rank values to the cluster categorical data. The k means algorithm assigns each point to the cluster whose center (also called centroid) is nearest. The center is the average of all points in the cluster i.e., its coordinates are the arithmetic mean for each dimension separately over all the points in the cluster. The objective function is given in Eq (4.4).

𝐽(𝑣) = ∑𝑐

∑𝑐𝑖 2

(4.4)

𝑖=1

𝑗=1 (‖𝑥𝑖 − 𝑣𝑗‖ )

‖𝑥𝑖 − 𝑣𝑗‖ is the Euclidian distance between 𝑥𝑖 and 𝑣𝑗

𝑐𝑖 is the number of data points in 𝑖𝑡ℎ cluster

𝑐 is the number of cluster centers.

# Algorithmic steps for k mean clustering:

Let X= {𝑋1, 𝑋2 … … … … 𝑋𝑛} be the set of data points and V={𝑉1, 𝑉2 … … … . 𝑉𝑐 } be the set of centers.

* 1. Randomly select ‘c’ cluster centers.
  2. Calculate the distance between each data point and cluster centers.
  3. Assign data point to the cluster whose distance from the cluster center is maximum of all the cluster centers.
  4. Recalculate the new cluster centers using Eq (4.5).

𝑣 = 1 ∑𝑐𝑖 𝑥

(4.5)

𝑖 𝑐𝑖 𝑗=1 𝑖

where 𝑐𝑖 represents the number of data points in the 𝑖𝑡ℎ cluster.

* 1. Recalculate the distance between each data point and new obtained cluster centers.
  2. If no data points were reassigned then stop, otherwise repeat from step 3.

1. **Fuzzy C-Means clustering:** This algorithm works by assigning membership to each data point corresponding to each cluster on the basis of distance between the cluster center and the

data point. Clearly, summation of membership of each data point should be equal to one. Aftereach iteration membership and cluster centers are updated according to the Eq (4.6) and Eq(4.7).

1

𝜇𝑖𝑗 =

( 2 −1)

(4.6)

∑𝑐

𝑑𝑖𝑗 𝑚

( )

𝑖=1

𝑚

𝑣𝑗

𝑘=1 𝑑𝑖𝑘

= (∑𝑛 (𝜇𝑖𝑗)

𝑗=1

𝑚

𝑥𝑖⁄

∑𝑛 (𝜇𝑖𝑗)

), j=1, 2…..c. (4.7)

where n is the number of data points.

𝑣𝑗 represents the 𝑗𝑡ℎ cluster center. m is the fuzziness index m ∈ [1,∞]

𝜇𝑖𝑗 represents the membership of 𝑖𝑡ℎ data to 𝑗𝑡ℎ cluster center.

𝑑𝑖𝑗 represents the Euclidian distance between 𝑖𝑡ℎ data and 𝑗𝑡ℎ cluster center. The main objective function to minimize is given in Eq (4.7).

𝐽(𝑣) = ∑𝑐

∑𝑐𝑖 𝑚 2

(4.8)

𝑖=1

𝑗=1(𝜇𝑖𝑗) (‖𝑥𝑖 − 𝑣𝑗‖ )

‖𝑥𝑖 − 𝑣𝑗‖ is the Euclidian distance between 𝑖𝑡ℎ data and 𝑗𝑡ℎ cluster center.

# Algorithmic steps for fuzzy c mean clustering:

Let X= {𝑋1, 𝑋2 … … … … 𝑋𝑛} be the set of data points and V={𝑉1, 𝑉2 … … … . 𝑉𝑐 } be the set of centers.

* 1. Randomly select ‘c’ cluster centers.
  2. Calculate the fuzzy membership 𝜇𝑖𝑗 using Eq (3).
  3. Compute the fuzzy centers 𝑣𝑗 using Eq (4).
  4. Repeat steps (2) and (3) until the minimum 𝐽(𝑣) value is achieved (or)

‖𝑈(𝐾+1) − 𝑈(𝐾)‖ < 𝛽, where k is the iteration step

𝛽 is the termination criterion between [0,1].

U is the fuzzy membership matrix J is the objective function.

# FCM-Based Methods with Intensity Inhomogeneity Correction.

**i) Bias corrected FCM:**

A modification in standard FCM objective function to deal with intensity inhomogeneity of brain MR images by introducing a term that allows the labeling of pixel to be influenced by the intensity of its immediate neighborhood. Neighborhood acts as a regularizer and biases the solution toward piecewise homogeneous labeling and is useful in segmenting MR images corrupted by salt and pepper noise. The modified objective function is given in Eq (4.9)

𝐽 = ∑𝑐

∑𝑁

𝜇𝑝 ‖𝑦

− 𝛽 − 𝑣 ‖2 + 𝛼 ∑𝑐

∑𝑁

𝜇𝑝 (∑ ‖𝑦

− 𝛽 − 𝑣 ‖2) (4.9)

𝑖=1

𝑘=1

𝑖𝑘 𝑘

𝑘 𝑖

𝑁𝑅

𝑖=1

𝑘=1

𝑖𝑘 𝑦𝗀𝑁𝐾 𝑟

𝑟 𝑖

where 𝑦𝑘 is the observed log transformation intensities at the 𝑘𝑡ℎ pixel and 𝑁𝑘 stands for set of neighbors that exists in a window around 𝑥𝑘 and is the cardinality of 𝑁𝑅. The effect of the

neighbor’s team is controlled by parameter𝛼. The relative importance of the regularizing term is inversely proportional to signal-to-noise (SNR) ratio of the MRI signal. Lower SNR would require a higher value of the parameter𝛼. The membership function, centroid, and bias field are updated according to the Eq (4.10) and Eq (4.11).

𝜇∗ = 1

(4.10)

𝑖𝑘

∑𝑐

((𝑑

+ (𝛼⁄𝑁 )𝛾 )⁄(𝑑

+ (𝛼⁄𝑁 )𝛾 )) 1⁄(𝑝−1)

𝑗=1

𝑖𝑘

𝑅 𝑖

𝑗𝑘

𝑅 𝑗

∑𝑁

𝜇𝑝 ((𝑦 − 𝛽 ) + (𝛼⁄𝑁 ) ∑ (𝑦

− 𝛽 ))

𝑣∗ =

𝑖

𝑘=1

𝑖𝑘 𝑘 𝑘

(1 + 𝛼) ∑𝑁

𝑅

𝜇𝑝

𝑦𝗀𝑁𝐾 𝑟 𝑘

(4.11)

𝑘=1 𝑖𝑘

∑𝑐 𝜇𝑝 𝑣

𝛽∗ = 𝑦

− 𝑖=1 𝑖𝑘 𝑖

(4.12)

𝑘 𝑘

∑

𝜇

𝑐 𝑝

𝑖=1 𝑖𝑘

where 𝑑𝑖𝑘 = ‖𝑦𝑘 − 𝛽𝑘 − 𝑣𝑖‖2 and 𝛾𝑖 = ‖𝑦𝑟 − 𝛽𝑟 − 𝑣𝑖‖2. The BCFCM outperformed the FCM on both simulated and real MR images. In noisy images, the BCFCN technique produced better results and compensates for noise by introducing a regularization term.

# HYBRID APPROACH

1. **MKIFCM ALGORITHM:**

The main idea of doing the integration between clustering techniques is to increase the quality and reduce runtime. In MKIFCM clustering technique, fuzzy c means can detect the tumor accurately, but it does more iteration that leads to a long time. Therefore, this proposed method integrated fuzzy c means with modified k means after applying dynamic histogram equalization technique based on advanced morphological operations. K means clustering is the most widely used clustering technique based on minimizing a formal objective function. Modifications to k means clustering method that makes it faster and more efficient are proposed. The main argument of the proposed modifications is on the reduction of intensive distance computation that takes place at each iterations of k means algorithm. To reduce the intensive distance computation, a simple mechanism by which at each iteration the distance between each data point and the cluster center nearest to it is computed and recorded in a data structure is suggested. Thus, on the following iterations, the distance between each data point and its previous nearest cluster is recomputed. The initialization process of the modified k-means algorithm as follows.

* 1. Randomly select a sample point from the data set as the first initialized cluster centroid.
  2. Select the remaining cluster centroids
     + Calculate the distance between each sample point in the sample and the cluster centroid that has been initialized, and then select the shortest distance among them.
     + Select the sample with the largest distance by probability as the new cluster centroid.
     + Repeat the above process until k cluster centroids are determined.
  3. For the k initial cluster centroids, the final cluster centroids are calculated using the k- means algorithm.

The following steps illustrate how modified k means integrated with fuzzy c means works.

*Read image*

*Apply histogram equalization technique*

*Apply dynamic histogram equalization technique Display the output of histogram equalized image*

*Display the output of dynamic histogram equalized image*

*Calculate the psnr value for both histogram equalization techniques Apply Gaussian filter*

*Apply median filter*

*Display the denoising image*

*Calculate the mse and psnr values for both Gaussian filter and median filter Skull removal process*

*Display the skull removal image Start MKIFCM algorithm*

*Find Cluster Center Mu Search for minimum value Calculating new centroid*

*Calculate IMG SIZE, max X, max Y Concatenate the dimensions*

*Save clustering image*

*Display clustering image MKIFCM image, execution time, and iteration numbers.*

# MARKFCM ALGORITHM:

An adaptive kernel-based fuzzy c means clustering with spatial constraints (ARKFCMS) model for image segmentation approach is proposed in order to improve the efficiency of image segmentation. Various experiments results shows that the proposed approach can get the spatial information features of an image accurately and is robust to realize image segmentation. An adaptively regularized kernel-based fuzzy c means clustering based on advanced morphological operations for segmentation of brain MRI images. The following steps illustrate how modified adaptively regularized kernel-based fuzzy c means works.

*Read image*

*Apply histogram equalization technique*

*Apply dynamic histogram equalization technique Display the output of histogram equalized image*

*Display the output of dynamic histogram equalized image Calculate the psnr value for both histogram equalization techniques Apply Gaussian filter*

*Apply median filter*

*Display the denoising image*

*Calculate the mse and psnr values for both Gaussian filter and median filter Skull removal process*

*Display the skull removal image Start MARKFCM algorithm*

*Set initial threshold*∈= 0.001*, m=2, loop counter t=0, v and u. Calculate the adaptive regularization parameter* 𝜑𝑖

*Calculate* 𝑋𝑖 *for MARKFCM1 and MARKFCM2*

*Calculate cluster centers* 𝑣(𝑡)*using* 𝑢(𝑡)

𝑗

*Calculate the membership function* 𝑢(𝑡+1)

*If max* ‖𝑢(𝑡+1) − 𝑢(𝑡)‖ <∈ *or t*<*100 then stop; otherwise update t=t+1 and calculate cluster centers*

𝑣(𝑡)*using* 𝑢(𝑡)

𝑗

*Save clustering image*

*Display clustering image MARKFCM image, execution time, and iteration numbers.*

1. **Experimental results and analysis**

## Data sets

In order to check the performance of our image segmentation approach, we used three benchmark data sets. The first one is the Digital Imaging and Communications in Medicine (DICOM) sata set. DICOM consists of 22 images that contain brain tumors. All DICOM images files are encoded in JPEG2000 transfer syntax with “.DCM” extension. The second data set is Brain Web data set; it contains simulated brain MRI data based on two anatomical models: normal and multiple sclerosis (MS). The files contained in this dataset have extension of “.MNC”. The last dataset is BRATS database from Multimodal Brain Tumor Segmentation. The dataset consists of multi-contrast MRI scans of 30 glioma patients (both low-grade and high- grade, and both with and without resection) along with expert annotations for “active tumor” and “edema”. This dataset contains 81 images. All of these datasets were opened by MIPAV and converted to “.JPG” extension.

## Results and discussion

In this section, show the results of our proposed image segmentation technique that obtained using real MRI brain images from three different data sets. This work was implemented using MATLAB 2019a. This experiments run on a core i7-4790 [CPU @3.90](mailto:CPU@3.90) GHz computer with 16 GB RAM.

## Testing the algorithm stability and robustness to noise.

Due to various factors such as noise and intensity inhomogeneity, the segmented images obtained using the above clustering algorithm may feature small holes or over segmentation. In addition, MR images are often corrupted by Gaussian noise, which greatly affects medical image segmentation. To improve the accuracy of segmentation, advanced morphological operations based on dynamic histogram equalization is proposed. However, a common disadvantage of conventional clustering algorithms is that they are sensitive to noise. To alleviate this shortcoming, Gaussian filter and median filter are used for preprocessing in this paper. After the

preprocessing, the MRI brain images are fed to the clustering stage. The preprocessing images of MRI which includes histogram equalization, dynamic histogram equalization, Gaussian filter, and median filter are shown in Fig.5.1.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| DS | Original MRI | HE | DHE | Gaussian filter | Median filter |
| DS1 BRATS |  |  |  |  |  |

Figure 5.1 preprocessing images of MRI which includes histogram equalization, dynamic histogram equalization, Gaussian filter, median filter.

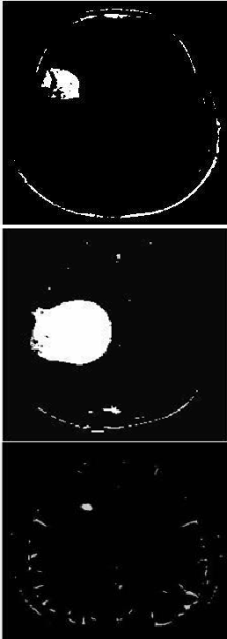
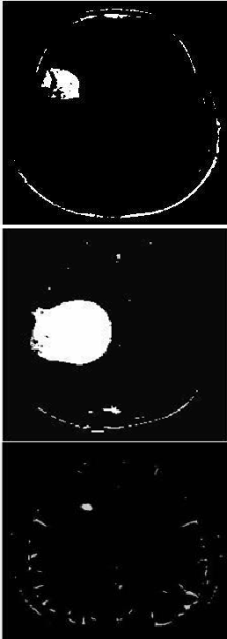
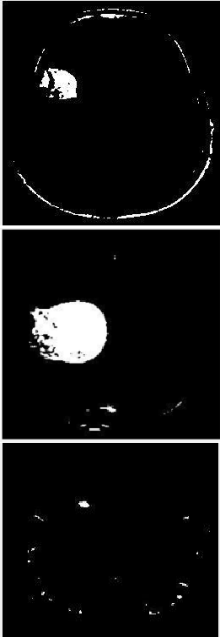
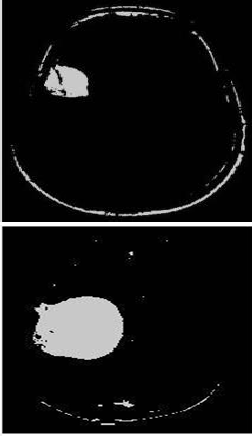
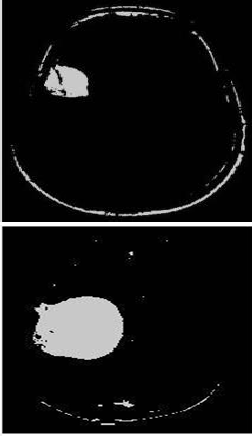
## Clustering stage.

Many clustering algorithms have been proposed recently. After the preprocessing stage, the MRI images are fed to the clustering stage. In this paper, we used five algorithms. We compare the proposed method with some commonly used clustering algorithms to verify the effectiveness of the proposed clustering algorithm. Fig.5.1 shows the preprocessing effect of MRI images which includes histogram equalization, dynamic histogram equalization, Gaussian filter, and median filter. The improved effect of dynamic histogram equalization when compared with histogram equalization and adaptive histogram equalization is shown in figure 4.3. After histogram equalization filtering process approach is done and the results shows better performance for the Gaussian filter is shown in f 4.4igure(f 4.4igure-Please check the usage). PSNR and MSE values are calculated for the Gaussian filter and median filter is shown in Table

* 1. Then, thresholding operation is done on the filtering images based on the equation given in
  2. The threshold image is shown in figure4.6. After that, clustering stage is adopted. In this paper, three clustering algorithms and two hybrid clustering algorithms based on advanced morphological operationsis performed.In hybrid approach, Modified K-means integrated with fuzzy C means is implemented. The algorithm first uses advanced morphological operations to remove the noise which reduces the computational complexity and the number of clustering iterations. In the clustering stage, the modified k-means clustering algorithm is exploited to initialize the clusters’ centroids. The problem of unstable clustering is solved, which arises owing to the uncertainty associated with initialization of cluster centroids. The sensitivity to clustering parameters is greatly reduced for the proposed algorithm and the algorithm’s robustness is further improved.

## Post processing

Impact of tumor from MRI brain image data remains an onerous task because of complex structure of brain tumors. To palliate the image artifacts such as noise, intensity inhomogeneity post processing technique is applied. To improve the segmentation accuracy, hole filling and median filtering are used for post processing. After the post processing, the small holes in the extracted tumor areas are filled and some missegmented areas are filtered. The results of the

segmentation algorithm after post processing are shown in Figure 5.2. The tumor extraction process is shown in Figure 5.3

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Dataset | KM | FCM | BCFCM | MKIFCM | MARKFCM |
|  |  |  |  |  |  |
|  |  |  |  |  |  |
|  |  |  |  |  |  |

Figure 5.2 Clustering results of the K-means, FCM, BCFCM, MKIFCM, and MARKFCM

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  |  |  |

Figure 5.3 Tumor extractions after post processing by using median filter.

## Performance Analysis

The comparison was done between the five tested techniques according to the following performance measures.

𝑇𝑟𝑢𝑒 𝑃𝑜𝑠𝑖𝑡𝑖𝑣𝑒 (𝑇𝑃) =

𝑁𝑜 𝑜𝑓 𝑟𝑒𝑠𝑢𝑙𝑡𝑒𝑑 𝑖𝑚𝑎𝑔𝑒𝑠 ℎ𝑎𝑣𝑖𝑛𝑔 𝑏𝑟𝑎𝑖𝑛 𝑡𝑢𝑚𝑜𝑟

𝑡𝑜𝑡𝑎𝑙 𝑛𝑜 𝑜𝑓 𝑖𝑚𝑎𝑔𝑒𝑠

𝑇𝑟𝑢𝑒 𝑁𝑒𝑔𝑎𝑡𝑖𝑣𝑒 (𝑇𝑁) =

𝑁𝑜 𝑜𝑓 𝑖𝑚𝑎𝑔𝑒𝑠 𝑡ℎ𝑎𝑡 ℎ𝑎𝑣𝑒 𝑛𝑜𝑡 𝑡𝑢𝑚𝑜𝑟

𝑡𝑜𝑡𝑎𝑙 𝑛𝑜 𝑜𝑓 𝑖𝑚𝑎𝑔𝑒𝑠

𝐹𝑎𝑙𝑠𝑒 𝑃𝑜𝑠𝑖𝑡𝑖𝑣𝑒(𝐹𝑃) =

𝑁𝑜 𝑜𝑓 𝑖𝑚𝑎𝑔𝑒𝑠 𝑡ℎ𝑎𝑡 ℎ𝑎𝑣𝑒 𝑛𝑜𝑡 𝑡𝑢𝑚𝑜𝑟 𝑎𝑛𝑑 𝑑𝑒𝑡𝑒𝑐𝑡𝑒𝑑 𝑝𝑜𝑠𝑖𝑡𝑖𝑣𝑒

𝑡𝑜𝑡𝑎𝑙 𝑛𝑜 𝑜𝑓 𝑖𝑚𝑎𝑔𝑒𝑠

𝐹𝑎𝑙𝑠𝑒 𝑁𝑒𝑔𝑎𝑡𝑖𝑣𝑒(𝐹𝑁) =

𝑁𝑜 𝑜𝑓 𝑖𝑚𝑎𝑔𝑒𝑠 ℎ𝑎𝑣𝑒 𝑡𝑢𝑚𝑜𝑟 𝑎𝑛𝑑 𝑛𝑜𝑡 𝑑𝑒𝑡𝑒𝑐𝑡𝑒𝑑

𝑡𝑜𝑡𝑎𝑙 𝑛𝑜 𝑜𝑓 𝑖𝑚𝑎𝑔𝑒𝑠

𝑇𝑃

𝑆𝑒𝑛𝑠𝑖𝑡𝑖𝑣𝑖𝑡𝑦 = (𝑇𝑃 + 𝐹𝑁)

𝑇𝑃

𝑆𝑝𝑒𝑐𝑖𝑓𝑖𝑐𝑖𝑡𝑦 = (𝑇𝑁 + 𝐹𝑃)

(𝑇𝑃 + 𝑇𝑁)

𝑎𝑐𝑐𝑢𝑟𝑎𝑐𝑦 = (𝑇𝑃 + 𝑇𝑁 + 𝐹𝑃 + 𝐹𝑁)

𝑇𝑃

𝑃𝑟𝑒𝑐𝑖𝑠𝑖𝑜𝑛 = (𝑇𝑃 + 𝐹𝑃)

𝑇𝑃

𝑅𝑒𝑐𝑎𝑙𝑙 = (𝑇𝑃 + 𝐹𝑁)

The following tables demonstrate the usefulness of our methodology in medical image segmentation by calculating accuracy, sensitivity, specificity, and recall. Comparison analysis of these measures for different datasets is shown in the given table. The performance analysis for the different algorithms KM, FCM, BCFCM, MKIFCM, and MARKFCM of dataset 1 is given in table 5.1. Table 5.2 shows the performance analysis for dataset2. Table 5.3 shows the performance analysis for dataset 3. From the table, it is clear that the clustering approach based on advanced morphological operation gives better results when compared with other approaches. From the table, it is also infer that the hybrid clustering approach based on advanced morphological operation shows better performances when with other three clustering algorithms.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Performance**  **analysis DS1** | **K means** | **FCM** | **BCFCM** | **MKIFCM** | **MARKFCM** |
| **Accuracy** | 0.8110 | 0.7012 | 0.7798 | 0.9271 | 0.9232 |
| **Sensitivity** | 0.8011 | 0.7101 | 0.7656 | 0.9212 | 0.9200 |
| **Specificity** | 0.8001 | 0.7222 | 0.7890 | 0.9111 | 0.9310 |
| **Recall** | 0.8110 | 0.7321 | 0.7888 | 0.9121 | 0.9391 |
| Table 5.1 performance | | | analysis for data set 1 | |  |
| **Performance**  **analysis DS2** | **K means** | **FCM** | **BCFCM** | **MKIFCM** | **MARKFCM** |
| **Accuracy** | 0.8443 | 0.7434 | 0.8111 | 0.9111 | 0.8999 |
| **Sensitivity** | 0.8512 | 0.7444 | 0.8100 | 0.9122 | 0.8909 |
| **Specificity** | 0.8441 | 0.7931 | 0.8222 | 0.9210 | 0.9010 |
| **Recall** | 0.8441 | 0.7712 | 0.8222 | 0.9209 | 0.9019 |
| Table 5.2 performance | | | analysis for data set 2 | |  |
| **Performance**  **analysis DS3** | **K means** | **FCM** | **BCFCM** | **MKIFCM** | **MARKFCM** |
| **Accuracy** | 0.7210 | 0.6665 | 0.7898 | 0.9090 | 0.8970 |
| **Sensitivity** | 0.7302 | 0.6777 | 0.7856 | 0.9111 | 0.8978 |
| **Specificity** | 0.7900 | 0.6931 | 0.7992 | 0.9212 | 0.9080 |
| **Recall** | 0.7881 | 0.6912 | 0.7989 | 0.9321 | 0.9121 |

Table 5.3 performance analysis for data set 3

## Validation

The segmented images using these algorithms were compared with the ground truth cases. The performance analysis is performed to compare the data with ground truth image. The performance analysis of accuracy, sensitivity, specificity, recall, and F-measure is calculated from segmentation. The research work is performed using five different algorithms. Among the entire algorithm, the proposed clustering algorithm based on advanced morphological operations provides better results. Then, the hybrid segmentation based on advanced morphological operations provides the best result and provide the accuracy when compared with other three algorithms because it integrates two algorithms, which integrates the distinct features of the two methods.

From the review of various articles, it can be identified that the integration of two algorithms leads to good result. K-means algorithms detect the tumor fast than FCM, but it provides good result only for smaller value of K. The next algorithm FCM is used to find tumor cells that are not connected by K-means. FCM is also not considering the spatial characteristics of images because this kind of characteristics is very important to classify complex structures. Next, a modification in FCM is proposed to deal with intensity inhomogeneity, but it takes long time to perform segmentation. Hence, the hybrid approach of clustering algorithm is proposed. From the previous figures and tables, it is very clear that our proposed technique provides best results when compared with other methods. Although MARKFCM is more accurate than KM, FCM, and BCFCM, MKIFCM is more accurate than MARKFCM. Figure 5.9 (a) shows the comparison analysis of different clustering algorithms. From the figure 5.9 (a),it is inferred from the graph that MKIFCM, MARKFCM shows better performance when compared with KM, FCM, and BCFCM. MKIFCM show inferior performance than MARKFCM for dataset1. The figure 5.9 (b) shows inferior performance of different clustering algorithms. MARKFCMand MKIFCM shows better performance compared with other three algorithms and the graph results implies MARKFCM shows inferior performance compared with MKIFCM for dataset2.Figure

5.9 (c) implies that compared with four algorithms, MKIFCM shows good performance for dataset3.

Next, analysis of the proposed system based on the time measurement is significant. So, based on this idea, the processing time of different clustering algorithms is calculated and the results of this analysis are shown in Figure 5.10. From the figure 5.10, it is clear that FCM- and FCM-based approach BCFCM shows lag time when compared with other three algorithms KM, MARKFCM, MKIFCM. K means shows good lead time results when compared with FCM- based approaches. It is also inferred that hybrid approaches shows good clustering performance when compared with KM, FCM, and BCFCM. From the figure 5.10, MARKFCM shows good clustering performance when compared with MKIFCM. Overall, the hybrid clustering approach shows better performance when compared with other clustering algorithms. Figure 5.11 shows the overall clustering performance analysis of different algorithms.

* + 1. ***Segmentation Accuracy*:** The performances of the proposed and other FCM-based approaches are compared with respect to the optimal segmentation accuracy which is defined as the sum of the correctly classified pixels divided by the sum of the total number of pixels:

𝑠𝑒𝑔𝑚𝑒𝑛𝑡𝑎𝑡𝑖𝑜𝑛 𝑎𝑐𝑐𝑢𝑟𝑎𝑐𝑦 = ∑𝑐

𝐴𝑖∩𝐶𝑖

(4.13)

𝑖=1 𝑐

∑

𝑗=1

𝐶𝑗

where 𝑐 is the number of clusters, 𝐴𝑖 represents the set of pixels belonging to the ith cluster by the segmentation algorithm, and 𝐶𝑖 represents the set of pixels belonging to the 𝑖th cluster in the reference segmented image. To evaluate the robustness of the proposed segmentation approach in noisy environment, we add different types of noise and different amount of noise to a T1- weighted brain MR image, shown in Figure (4.4). All test images are corrupted by 8% and 10% Gaussian noise, speckle noise, and 10% and 12% salt and pepper noise as shown in Figure (4.4) and table (4.2).The proposed algorithm increases 4.09% (MKIFCM) and 4.87% (MARKFCM) of the segmentation accuracy for a noise-free brain MR image compared with the baseline performance, where we used the average value of the segmentation accuracy as a baseline. For noise-inserted images, the proposed algorithm achieves 7.13%–13.33% (MKIFCM) and 7.52%– 15.03% (MARKFCM) improvements in the segmentation accuracy, which is significant in the field of image segmentation for diagnosis purpose.

## Calculating the area of tumor:

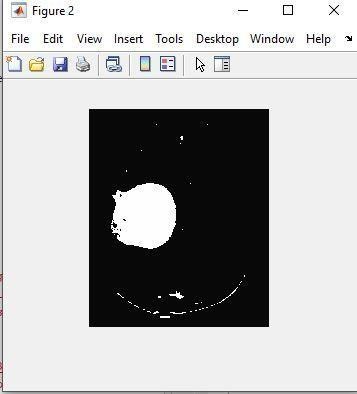


Figure 5.8 calculating the area of tumor by using MATLAB Number of total pixels are = 22243

Number of white pixels are=1167 Number of black pixels are=33425 The ratio is 0.0267

Area of tumor is = 1.3056e+002

1

0.8

0.6

0.4

0.2

0

K means

FCM BCFCM MKIFCM

MARKFCM

Accuracy Sensitivity Specificity Recall

Figure 5.9 a. Performance analysis of clustering algorithms for dataset1.

1

0.5

K means

FCM BCFCM MKIFCM

0

Accuracy Sensitivity Specificity

Recall

MARKFCM

Figure 5.9 b. Performance analysis of clustering algorithms for dataset2.

1

0.8

0.6

0.4

0.2

0

K means

FCM BCFCM MKIFCM

Accuracy Sensitivity Specificity

Recall

MARKFCM

Figure 5.9 c. Performance analysis of clustering algorithms for dataset3.

70

60

50

40

30

20

10

0

KM

FCM BCFCM MKIFCM

MARKFCM

MR IMAGE 1 MR IMAGE 2 MR IMAGE 3 MR IMAGE 4

Figure 5.10 Processing time of clustering algorithms

100

80

60

40

20

KM

FCM BCFCM MKIFCM

MARKFCM

0

Category 1

Category 2

Category 3

Category 4

Figure 5.11Comparison analysis of clustering algorithms based on accuracy, sensitivity, specificity, recall, and F measure.

## Conclusion:

Image segmentation plays a significant role in medical image diagnosis. Among the medical image modality, MRI is the most effectively image model used for diagnostic purposes. When compared with CT scan, MRI scan is more comfortable for diagnostic purposes. In this paper, a hybrid approach of clustering algorithm based on advanced morphological operations is proposed. Here, segmentation of brain tumor images based on five clustering approaches namely, KM, FCM, BCFM, MKIFCM, and MARKFCM carried out. K-means algorithm can detect a brain tumor faster than FCM but FCM can predict tumor cells accurately. On the other hand, FCM fails to segment images corrupted by noise, outliers, and other imaging artifacts. So, a new hybrid approach based on advanced morphological operations is proposed. From the experimental results, it is proved that the effectiveness of our approach brain tumor segmentation by comparing it with other methods. The performance of the proposed technique, its minimization time strategy and its quality has been demonstrated in several experiments. In future, to increase the efficiency of the segmentation results, an intensity-adjustment process will be carried out.

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