

# Brain Tumor Detection Using Clustering Algorithms in MRI Images

Nikhita Biradar<sup>1</sup>, Prakash H. Unki<sup>2</sup>

<sup>1</sup>M.Tech Student, Dept. of Computer Science and Engineering,  
BLDEA's V.P. Dr. P.G. Halakatti College of Engineering and Technology, Vijayapur, Karnataka, India

<sup>2</sup>Associate Professor, Dept. of Computer Science and Engineering,  
BLDEA's V.P. Dr. P.G. Halakatti College of Engineering and Technology, Vijayapur, Karnataka, India

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**Abstract** - Brain tumor is an accumulation of abnormal cells in the brain. Detection of tumor from magnetic resonance imaging (MRI) brain scan is one of the most promising research topics in medical image processing. This paper presents a novel tumor detection system in MRI images using k-means technique integrated with Fuzzy c-means (FCM) clustering algorithm and artificial neural network (ANN). ANN is used to classify the MRI images into two categories; normal and tumor image. The proposed system takes benefit of both integrated algorithms in the aspect of minimal computation time and accuracy. It accurately extracts the tumor region and calculates the tumor area. The accuracy is calculated by comparing results with the ground truth (GT) of processed image.

**Key Words:** Magnetic resonance imaging (MRI), k-means clustering, fuzzy c-means (FCM) clustering, artificial neural network (ANN), ground truth (GT).

## 1. INTRODUCTION

Brain tumors are formed by collection of abnormal cells that grows uncontrollable. Diagnosis of brain tumors is done by detection of the abnormal brain structure. The internal structure of brain can be viewed by magnetic resonance imaging (MRI) and computed tomography (CT) scans. Compared to CT scan, MRI scan is more efficient and it doesn't affect the patient body as no radiations are used. MRI scanning is done by using radiofrequency and magnetic field [1]. MRI images are analyzed by the radiologists to diagnose the tumor. Segmentation of images is important as large numbers of images are generated during the scan and it is unlikely for clinical experts to manually divide these images in a reasonable time.

Image segmentation refers to segregation of given image into multiple non-overlapping regions. Segmentation represents the image into sets of pixels that are more significant and easier for analysis. It is applied to approximately locate the boundaries or objects in an image and the resulting segments collectively cover the complete image [2]. The segmentation algorithms works on one of the two basic characteristics of image intensity; similarity and discontinuity [3]. In the former, segmentation technique is based on dividing an image into set of pixels that are similar to the some predefined criteria. The latter partitioning works

on the changes in intensity of an image, such as corners and edges. Segmentation has a significant part in clinical diagnosis and can be useful in pre-surgical planning and computer assisted surgery. Therefore, numerous segmentation techniques are available which can be used widely, such as threshold based segmentation, histogram based methods, region-based (region growing, splitting and merging methods), edge-based and clustering methods (expectation maximization, k-means, FCM and mean shift) [4]-[6]. Clustering methods are most promising technique for processing the medical images. Cluster analysis can be set out as a pre-processing stage for other methods, namely classifiers that would then run on selected clusters [7]. Therefore in our system, we have used clustering segmentation techniques for diagnosis of tumor and calculating tumor area in MRI images.

This paper presents an effective tumor detection system for MRI images by integrating k-means with FCM clustering techniques. This system gets benefit of the k-means in the aspect of minimal computation time and fuzzy c-means in the aspect of accuracy. k-means algorithm is to perform the initial segmentation. Then, on the criteria of updated membership set and exact cluster selection, an approximate segmented tumor is located from FCM technique. Even the minute changes in intensities of normal and tumor tissue is recognized by this method. ANN classifies MRI into two categories, normal image and image with tumor by preparing pertinent training, target data. Finally, the reliability of the system is calculated by comparing the result with GT of the processed image. Essential utilization of this technique is to get measure and location of tumor, which will help in organizing of treatment and surgery.

## 2. RELATED WORK

Many researchers have suggested several methodologies and procedures for medical image segmentation and techniques for tumor detection. These include region growing, thresholding, mean shift methods, clustering and statistical model.

H. Suzuki and J. Torwaki [8], developed an algorithm for automatic segmentation of head MRI images using thresholding techniques. The algorithm consists of three incremental steps; histogram analysis to locate the brain and next step is to create a mask using nonlinear anisotropic

diffusion and thresholding to segregate brain from detected head region. Finally active contour model is applied to detect intracranial boundary.

Bandhyopadhyay sk, paul [9], proposed a segmentation technique based on k-mean clustering with dual localization that effectively segment tumor from brain MR images. After optimal segmentation, histogram and line scan method are applied to estimate breadth, length of tumor along xy-axis.

Shen, William sansharm [10], designed a fuzzy brain tissue segmentation method by applying new extension to FCM. In segmentation, they considered two influential factors to address the issues in neighborhood attraction. Finally, proposed techniques were tested for simulated, square and hospital collected MR images, at different noise levels.

Lemieux, G. Hahemann et al. [11], presented an automatic segmentation technique for brain in T1-weighted MR imaging data by applying thresholding and morphological operations. Their segmentation technique is independent of imaging scan orientation. They evaluated the performance by comparing results with semi-automated measurements.

Noreen, Hayat and S.Madami [12], introduced a technique to segment MRI images using discrete wavelet transform (DWT) and FCM. They extracted high pass image by applying DWT, which is robust to noise and FCM further enhance edge details in an image. This combination carries benefit of both the algorithms and gives better segmented result.

### 3. CLUSTERING TECHNIQUES FOR IMAGE SEGMENTATION & CLASSIFIER

The clustering segmentation techniques used here are k-means and fuzzy c-means (FCM). In k-means a pixel point belongs to only one cluster, where as in c-means with certain probability it may belong to more than cluster. Classification is an important technique used widely to differentiate normal and tumor brain images.

#### 3.1 k-means clustering

k-means clustering aims to divide the set of pixels  $X = \{x_i | i=1, 2 \dots, N\}$  into k clusters [13]. It supports multidimensional vectors and has highest computational efficiency. Initially the no. of cluster values are defined as k. Then k cluster centers  $C = \{c_j | j=1, 2 \dots, k\}$  are chosen randomly. Euclidian distance is calculated between each pixel point to each cluster centers using Eq.1.

$$d = \| x_i - c_j \| \tag{1}$$

Next, the pixel point is assigned to the cluster which has minimal distance among all. Then the new cluster centers are re-calculated. Again pixel distances are compared and re-assigned to new clusters. The process continues until no points were reassigned. The output of this technique is cluster image where each pixel belongs to one of the closest

cluster. The main merits of this technique are its simplicity and minimal computational time.

#### 3.2 Fuzzy c-means (FCM) clustering

FCM is introduced to divide the set of pixels  $X = \{x_1, x_2, \dots, x_N\}$  into C fuzzy clusters where each point has a degree of belonging to clusters. It allows a point to belong to more than one cluster as per its membership value. It is an iterative process for minimizing objective function, related to fuzzy membership set U of cluster centers C:

$$J = \sum_{i=1}^N \sum_{j=1}^C u_{ij}^m (x_i - c_j)^2 \tag{2}$$

Where,  $u_{ij}$  is the membership table, m is a cluster fuzziness factor and  $(x_i - c_j)$  is euclidean distance.

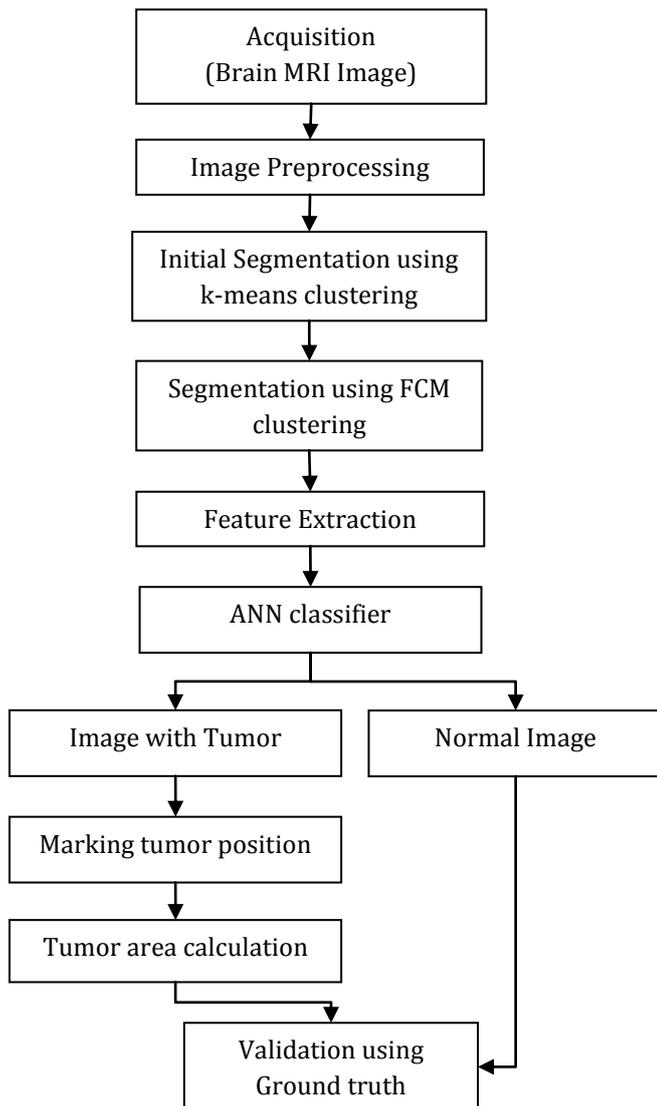
The data points nearer to center of cluster have highest degree of membership than the points on edge [14]. FCM initially guess the cluster centers and assigns every point a membership grade for each clusters. Then, it moves the cluster center to right location by iteratively updating the centers within a data set. The membership defines the fuzziness of an image and also defines information contained in an image.

#### 3.3 Artificial Neural Network (ANN) classifier

ANN is a computational model inspired by functional and/or structural aspects of the biological neural networks. The artificial neurons are organized into 3-layers; input, hidden and output layer. The algorithm uses multi-layer interconnected units of artificial neurons (processing elements), to solve the specific problem. Classification involves feature extraction which gives important characteristics of an image. The classification process is split into training/learning phase and the testing stage. In the training, features are extracted from the diagnosed (known) images and are stored in knowledge base. Then in testing, the features of unknown image are compared with the stored data for classification.

### 4. PROPOSED SYSTEM

The proposed tumor detection system gets benefit from last two algorithms. The main motivation for combining these algorithms is to reduce the total iterations done by initializing exact cluster to the FCM clustering. Fig -1 describes the entire flow for detecting tumor in brain MRI images.



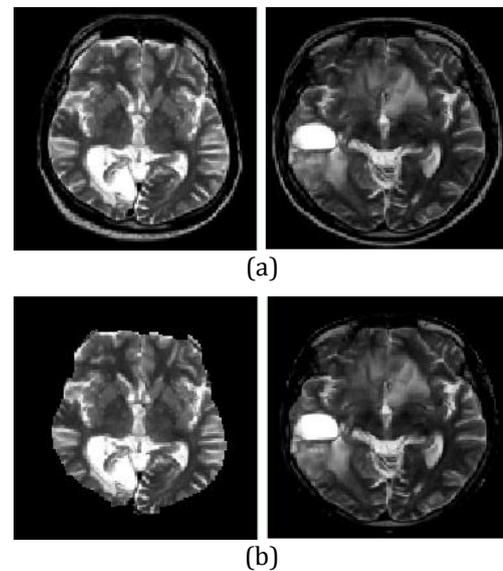
**Fig -1:** Block diagram for proposed tumor detection system

In this block diagram, initially we perform acquisition of brain MRI images. Images are preprocessed for removing noise and skull part using erosion and dilation morphological techniques. The output of this step is noise-free MRI containing only the brain part. The processed image is given as input for segmentation step where, the combination of k-means and fuzzy c-means clustering algorithms are used. In feature extraction stage, we have extracted different features from sharpened image like entropy, energy, contrast, intensity, homogeneity, etc. These features are used as an input to classifier for tumor detection. The neural network classifier is applied to classify the brain MRI images. If the brain image has the tumor region, then the image is further processed to detect the tumor accurately. Next, the tumor region is marked using morphological operations and area of the tumor region is calculated. Finally in validation stage, segmented image by integrated k-means and FCM are compared to the ground

truth (GT) of the processed image. The results are assessed by performance matrix that contains the accuracy, sensitivity and specificity.

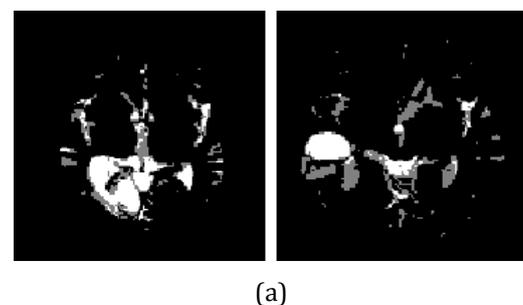
### 5. RESULTS AND DISCUSSION

In the proposed system, detection of tumor in MRI images is done using combined k-means and FCM clustering techniques. When the input image is loaded, preprocessing is done for the removal of noise and skull part using the morphological operations. The resulted image of the preprocessing step is as shown in Fig -2.



**Fig -2:** (a) Original input images (b) preprocessed images

After preprocessing step, the image is given as input to the image segmentation process. The integrated k-means and FCM clustering technique is applied to get the segmented image. k-mean clustering divides the preprocessed image into the clusters having same or nearby intensity values. Therefore it reduces the total iterations by initializing proper cluster to the FCM clustering and the region of interest is detected and segmented to separate image as shown in Fig -3.



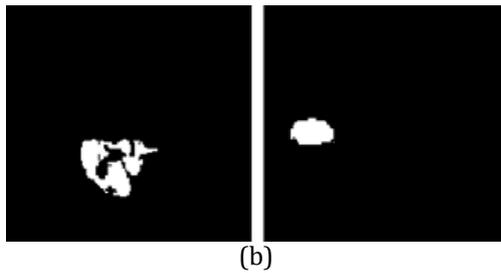


Fig -3: (a) Output of combined k-mean and FCM technique (b) Final segmented result

Image classification has been done by extracting different features like energy, entropy, homogeneity etc. The MRI image is classified into two categories, normal and abnormal brain image. If the MRI image has the tumor then the tumor region is marked using morphological operation and also the area of tumor is calculated. The below table -1 depicts the extracted feature and calculated tumor area for sample images.

Table -1: Feature Extraction and calculated tumor area

| Features                      | Sample Image 1 | Sample Image 2 |
|-------------------------------|----------------|----------------|
| Energy                        | 3.43e-03       | 1.02e-03       |
| Contrast                      | 1.92e+03       | 2.53e+02       |
| Entropy                       | 5.68e+00       | 6.89e+00       |
| Homogeneity                   | 2.30e-02       | 1.32e-01       |
| Dissimilarity                 | 4.33e+01       | 1.33e+01       |
| Calculated Tumor Area (pixel) | 296            | 992            |

The tumor region is marked using morphological operations. The output image of the detection process is as shown in Fig -4.

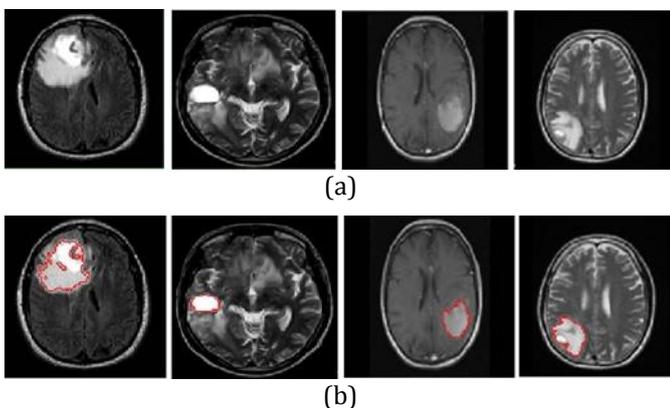


Fig -4: (a) Input image with tumor (b) Detected brain tumor images

In validation stage, experimental results of the system are compared with GT of the processed image. This comparison

is assessed by performance matrix that contains accuracy, sensitivity and specificity. The performance matrix for two sample input images is listed in table -2.

The accuracy, sensitivity and specificity are calculated using following equations:

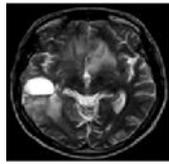
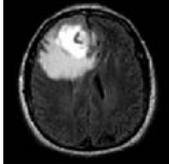
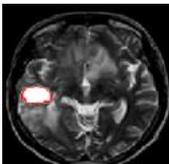
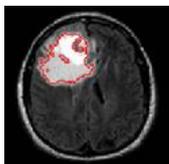
$$\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FN+FP)} \quad (3)$$

$$\text{Sensitivity} = \frac{TP}{(TP+FN)} \quad (4)$$

$$\text{Specificity} = \frac{(TN)}{(TN+FP)} \quad (5)$$

where, True Positive (TP)= intersection between resulting image and GT, False Positive (FP)= output segmented image not overlapping the GT, False Negative (FN)= missed part of GT and True Negative (TN)= part of image beyond the union output image + GT.

Table -2: Performance matrix (Validation of results by comparing it with GT of the processed image)

|                    |   |   |
|--------------------|---|---|
| Sample Input Image |  |  |
| Output Image       |  |  |
| Accuracy           | 0.99866   | 0.98474   |
| Specificity        | 0.97872   | 0.92209   |
| Sensitivity        | 0.99895   | 0.98821   |

## 6. CONCLUSION

In this work, we have presented a new methodology for detection of tumor in MRI images by combining k-means and FCM techniques. It is applied to remove the constraints of the k-mean and FCM clustering algorithms. The classification of tumor in MRI image is done using artificial neural network (ANN) based on similarity between the feature vectors. ANN classifies the brain MRI images into two categories, normal and tumor images. In this approach, k-mean algorithm is used to perform the initial segmentation of MRI images. On the criteria of updated membership set and appropriate cluster selection, a final segmented tumor image is obtained using FCM. The segmented tumor region is marked and the

tumor area is calculated. The effectiveness of the current method is determined by comparing results with GT of the processed image. The experimental results clarify that the suggested approach gives better segmentation result and accuracy in minimal execution time.

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