Novel Center Symmetric Local Binary Pattern And Chi Square Fuzzy C-Mean Clustering Based Segmentation In Medical Imaging Technique

G. Anand Kumar, P. V. Sridevi

Abstract: Accurate brain tumor segmentation is a challenging task from the Magnetic Resonance Imaging (MRI) in the field of medical image processing. For this purpose, we propose a Novel Center Symmetric-Local Binary Pattern (CS-LBP) and Chi Square Fuzzy C-mean based segmentation via clustering to segment the abnormal tissues from the normal region. Initially, preprocessing is performed to extricate the region of interest based on improved threshold and center symmetric LBP. Then we compare the preprocessing output and original MRI image using Bhattacharya similarity metrics to obtain the region of interest from the imaging technology. Finally, Chi Square distance based Fuzzy C-Mean (CS-FCM) segmentation is performed to cluster the region according to the feature based on region of interest (ROI), including entropy, contrast, and mean for necrosis, edema and enhanced tumor regions. BRATS 2015 dataset is used to evaluate the performance in terms of Jaccard matching, specificity, Positive Predictive Value (PPV) and Dice Similarity Coefficient (DSC). The existing approaches are not efficient and predictive whereas our proposed method performs better in clustering the tumor into three regions (necrosis, edema and enhanced tumor) based on the region of interest.

Index Terms: image clustering, brain tumor segmentation, fuzzy algorithm, threshold, magnetic resonance imaging

1 INTRODUCTION

Tumor is defined as the abnormal, uncontrolled growth of tissue in the brain that affect the human health condition. Brain tumors can be detected and diagnosis with the help of the MRI brain images obtained by using the medical image technologies. Brain tumor could be curable when it detecting in the earlier stage else this is a series threat to human life. Medical MRI [1] is used by the physician to find abnormalities in the human body, diagnosing and provide earlier treatment to them. An accurate segmentation of brain tumors has a great impact in computer-aided diagnosis and treatment planning. The most frequently used imaging technique is MRI used to segment and predict the tumor region divides an MRI image into the component object or region. In the traditional approaches, physician, radiologist and neurologist detecting the abnormalities and diseases from the manually obtained information from the images. Now a day's to improve the accuracy for detecting the brain diseases and abnormality numerous automatic approaches have been developed.

Normally brain tumor image contain large amount of information's so manual segmentation is time consuming and complex process. In order to overcome these complication, automatic segmentations methods were introduced to detect the of brain tumor such as region growing [2], thresholding [3], artificial neural network [4] and clustering [5], etc. But still segmentation of brain tumor is still a challenging problem in image processing and analysis. The structure of the brain is complicated so it is difficult to determine the accurate segmentation of necrosis, edema and enhanced tumor. Several tissues present in the brain consist of three normal tissue [6] region, namely, gray matter (GM), white matter (WM), and Cerebrospinal Fluid (CSF), which is significant to analysis and treatment for diseases such as multiple sclerosis, Alzheimer's disease and epilepsy. These three regions are identified by the segmentation of brain image by utilizing the gray level distribution of pixels. The main goal of brain tumor segmentation [7] is to identifies the extensive and location of the tumor region [8], such as edema, active tumorous tissue and necrotic tissue. Mean-shift algorithm [9] were used to detect the brain tumor in MRI image. The most widely used automatic segmentation technique in bioinformatics application [10] is clustering. Now a days, clustering based image segmentation on pixels are used in imaging technique, which organizing a given database into a group. Significant role of clustering in MRI image is generally used to detect the brain diseases and abnormalities, to monitor, diagnose and treat disease. Several clustering technique are used in the existing work to detect the abnormalities such as fuzzy k-mean clustering [11], , adaptive fuzzy k-mean clustering [12], modified k-mean clustering [13] and fuzzy C-mean [14] clustering. The goal of these clustering is to detect the abnormalities based algorithm to minimize the objective function based on certain criteria. In this paper, we introduce a Novel center

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symmetric local binary pattern (LBP) and chi square fuzzy C-mean based segmentation via clustering method. First, input MRI image is divided into $n \times n$ block, then improved threshold is used to find the tumorous and non-tumorous block from the image. The center symmetric LBP is used to extract the feature based on the tumorous block. Then compare this resultant tumorous block with the original image to obtain the region of interest. At last, Chi-square FCM clustering method is used to segment the regions (necrosis, edema and enhanced tumor) based on feature from the ROI. Finally, segmentation via clustering the MRI image is obtained using BRATS 2015 dataset and evaluate the performance based on Jaccard matching, specificity, PPV and DSC.

Significant contribution of the paper

- First, we take the input MRI image and partition it into $n \times n$ similar size blocks.
- Second preprocessing step can be carried out using improved threshold method to evaluate the tumorous and non-tumorous block based on the input block image.
- Third to extricate the feature relevant to tumorous block by using center symmetric LBP. Then comparing the result from the center symmetric LBP and original image to produce the region of interest.
- Finally chi-square FCM clustering method is used to segment the region related to three tissue, namely, edema, necrosis core and enhancing tumor.

The outline of the paper is as follows: - Section 2 describes the related works**.** Section 3 proposes Center symmetric local binary pattern and chi square fuzzy C-mean clustering and its preprocessing method to extricate the region of interest in detail. Section 4 discusses the simulation and performance evaluation of segmentation via clustering. Finally, we conclude our work in section 5.

2 RELATED WORK

Zhao *et al.* [15] introduce a novel method for brain tumor segmentation, which integrates both conditional random fields and fully convolutional neural networks to produce the result with spatial consistency and good appearance. In this, train these network using image slices and 2D image patches, which consists of three steps for segmentation. First, image patches could be used to train fully convolutional neural networks. Then image slices were used to train the Conditional Random Fields. At last these two network were fine-tuned using image slices from coronal, sagittal view and axial view respectively. In addition, voting based fusion strategy could be used to segment the brain image. There methods were still had some performance degradation, to overwhelm this, we propose a novel Center symmetric LBP and chi square fuzzy C-mean clustering based segmentation in MRI image to enhance the performance and accuracy in imaging technology. Ding *et al*. [16] presented a multimodal image segmentation based stacked de-noising auto-encoders (SDAE), which extricate different tumor tissue from normal tissue from various modality images. BRATS dataset adopted bottom hat and top hat transformation were used for preprocessing the patches to enhance the image contrast. After preprocessing, SDAE is applied to get the model parameter, then Gray level patches were given as the input for the deep neural learning to acquire the segmentation result. Finally, overshoot area could be eliminated using threshold method on the segmented image. As a consequence, performance of the SDAE method was degraded due to the texture feature was not used in modality image. Shivhare *et al*. [17] introduced a fully automatic segmentation and detection based parameter free clustering. This technique consist of two main module: parameter-free clustering and morphological operation. T1c modality of image was taken as an input and cluster based on K-mean algorithm. Then in the morphological process, clustered input was applied to dilation and hole filling operation to obtain the segmented tumor region. In this, performance evaluation can be achieved by using BRATS 2015 challenge dataset. Kumar and sridevi [18] introduce a novel T-Spline intensity inhomogeneity correction and 3D deep learning for automatic brain MR tumor segmentation. It comprises four steps, initially preprocessing is applied which diminish the bias field distortion, intensity variations and noises. Secondly feature extraction is performed by extended gray level co-occurrence matrix (GLCM) to extract the texture patches for segmentation. Then, automatic segmentation was adopted to divide the abnormal tissue from the raw data. Finally, thresholding based post-processing scheme were utilized to determine the segmentation results, which eradicate the small cluster in the segmentation result which classify the tumor mistakenly. In this, the performance metrics such as Jaccard index, specificity, PPV, dice similarity coefficient, sensitivity and accuracy are evaluated by standard BRATS 2015 dataset for segmentation. Bal *et al.* [19] introduced a fuzzy-possibilistic C-means (FPCM), which integrate both fuzzy C mean and possibilistic C mean were accurately segment the brain tumor in MRI images. For accurate determination of tumor region in an image, shape based topology could be used. Initially preprocessing step could be performed, patch based K-means algorithm was used to eliminate the skull from the MRI image. Once the skull stripping is performed, FPCM was applied over the brain tissue and tumor region in the brain. Finally, shape based feature was used to segment the brain tumor from the original image. Shen *et al.* [20] introduce a three fully convolutional networks to segment the brain tumor using BRATS 2015 dataset. They follow three major step i.e.) preprocessing, segmentation and post processing. In this, mean filter, median filter and Gaussian filter were used to preprocess the Multimodality MR images. After the completion of preprocessing, output from the three network could be combined. Finally for post processing they use Fully Connected Conditional Random Field to determine the minute structure after segmentation. Here, BRATS 2015 dataset is used to evaluate the performance metrices such as dice and sensitivity.

3. CENTER SYMMETRIC LOCAL BINARY PATTERN AND CHI SQUARE FUZZY C-MEAN CLUSTERING

For segmentation via clustering, we introduce a Novel center symmetric LBP and chi square fuzzy C-mean in imaging technology. The proposed method process is classified into three stages as preprocessing, feature extraction and segmentation. Fig.1 show the proposed architecture for segmenting the MRI images into edema, necrosis and enhancing tumor regions. Initially *a) preprocessing* is performed by splitting the MRI image into $n \times n$ similar size blocks and tumor region is detected by means of improved threshold method and then *b) ROI extraction* is performed based on center symmetric LBP method. Finally, c) *Chi-square FCM clustering method* is used to segment the image based on edema, necrosis and enhancing tumor regions.

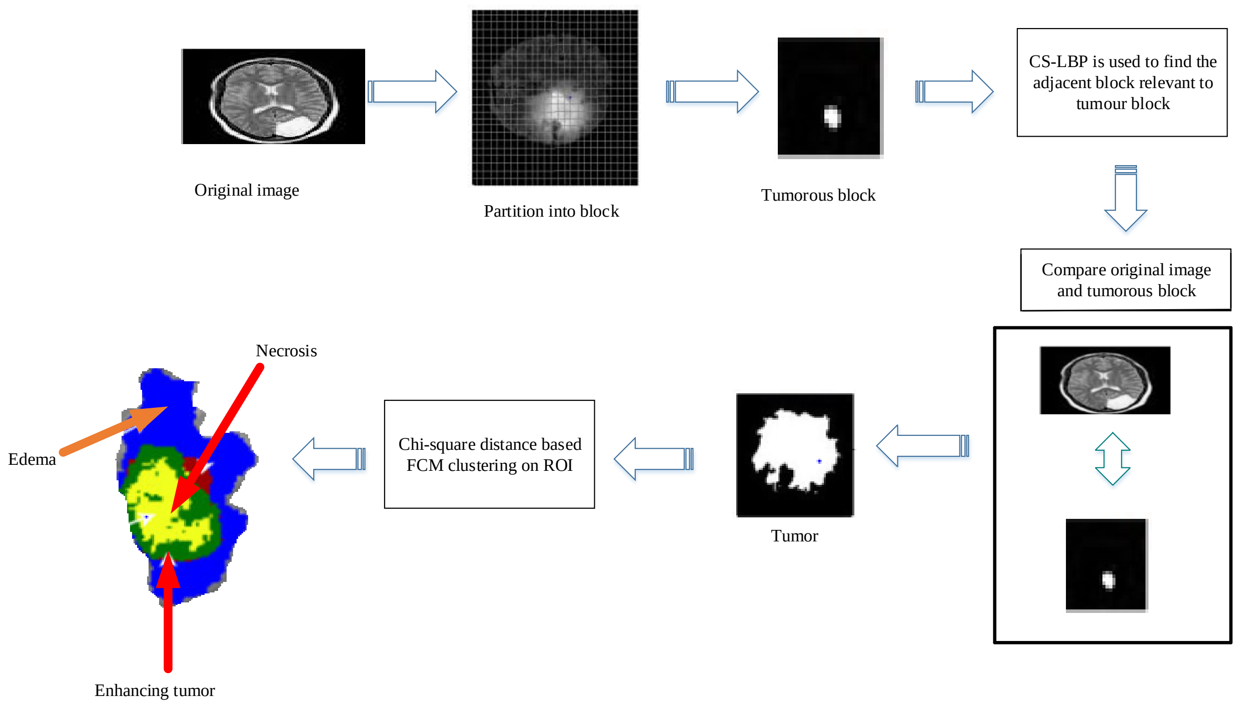


Figure 1: Segmentation via clustering the brain MRI image

3.1 Preprocessing

Initially, we read the brain tumor image from the medical imaging technology. Here we divide an image into similar sized blocks $b_1, b_2, b_3, \cdots, b_m$, where m represents the number of block in an image and the pixel intensity value as $I_1, I_2, I_3, \cdots I_p$, where p be the number of pixel in an image. After partitioning, the tumorous block is segmented by means of the improved thresholding function.

Threshold based Segmentation: Threshold method is simplest and important in image segmentation process, which is very sensitive to noise. This method is based on pixel with identical intensity value to detect the specified region. Then the output of this approach obtains the binary image is based on the given gray scale image. There are two types of thresholding methods normally used for segmentation, namely, global and local. In global threshold have some limitation when segment the object and threshold that image contrast is low and threshold selection is difficult. But we use local threshold to determine the specified threshold value based on the intensity value of the image.

Let us consider block of the image be G(x, y) and the threshold value be F, then the segmented image is represented as S(x, y).

$$S(x,\ y) = \begin{Bmatrix} 1, & \text{if } G(x,\ y) > F \\ 0, & \textit{if } G(x,\ y) < F \end{Bmatrix} \tag{1}$$

By using this threshold value, we distinguish the object and their background from the block of image pixels. If the image G(x, y) is larger than the threshold value it is denoted as 1 otherwise 0. By choosing the threshold value (F) based on the improved threshold as follow as,

$$F = \frac{\max(\ G(x,y) + \min\ G(x,y))}{2} \tag{2}$$

Improved threshold method is used to determine the tumorous (T) and non-tumorous (NT) region. Here, white color represents the tumorous region and black color represent the non-tumorous region.

Determination of Tumor block: Tumor from the block of the image is determined by using the threshold segmentation. The neighboring block have the same feature like the tumor block are extracted from the input MRI image. For this, the common LBP based feature extraction method is used to extract the feature based on the adjacent block. Here, the Local spatial relationship between center pixel and neighboring pixels are given by this operator. In the local binary pattern the image is divided into small same size cells. Each cell has eight neighboring pixels and the comparison can be made by using the center pixel and the neighboring pixel. But in CS-LBP, the pixel value compared with the symmetrically opposing pixel w.r.t the center pixel.

$$C_{sym}\ LBP = \sum_{z=0}^{N} c(p_z - p_{(z+N)})2^z \tag{3}$$

$$c(y) = \begin{Bmatrix} 1, & for\ \ y > T \\ 0, & othewise \end{Bmatrix} \tag{4}$$

Where $p_z - p_{(z+N)}$ related to the gray value of center symmetric pair of pixel. Here the data region is taken between 0 and 1, and the value of T is fixed to 0.01. Compared with the LBP, dimensionality of the CS-LBP will be reduced and it hold better gradient information. Finally, we determine the tumorous block by using CS-LBP method.

3.2 ROI extraction

In this, the tumor block acquired by using the CS-LBP and the original image are compared to form the Region of interest (ROI) as illustrate in figure 1. Next, we calculate the similarity between the original image and the tumorous block Bhattacharya similarity metric and it is determined as,

$$B(h(O), h(T)) = \sum h(O) * h(T) \tag{5}$$

Where h (O) be the original image and h (T) be the tumorous block.

ROI Clustering based on edema, necrosis and enhancing tumor: Feature extraction transform the input data into the more manageable features, which contains the information related to size, color and texture. Feature can be extricated from the region of interest using numerous methods such as texture features, color features, spatial features, and transform features. In the MRI brain images, texture based feature is the important characteristic in the identification of ROI. This proposed approach utilize an enhanced GLCM technique to extricate the feature from the texture patches for every sequence. For segmentation purpose, GLCM feature technique extract the particular feature and forms a matrix. This particular feature is used for segmentation of tissue structure. After ROI extraction, clustering is performed by CS-FCM method to cluster the MRI images into edema, enhanced tumor and necrosis regions.

3.3 Chi-Square based Fuzzy C-Mean Segmentation

FCM algorithm partition the finite collection of data point based pixel value into C fuzzy cluster with respect to the given criteria. Let $x = x_1, x_2, \cdots x_n$ be the set of data point from the image pixel to be clustered into c fuzzy cluster. Various fuzzy clustering methods have been developed to segment the image and most of them based on distance criteria. In this work, we introduce a chi-square FCM algorithm for the segmentation through clustering in the MRI image. Here, the execution time of chi-square distance is better than the Euclidean distance measurement and the membership function of fuzzy logic value ranges from 0 to1. There is no sudden changes occurs between non-membership and membership function. The main goal is to minimize the objective function (J_{cf}) of CS-FCM algorithm and is calculated as follows,

$$J_{cf} = \sum_{i=1}^{c} \sum_{j=1}^{m} F_{ij}^{\ w} s_{ij}^{\ 2} \tag{6}$$

Where m is the number of pixel in the ROI image, c is the number of clusters, F_{ij} is the membership function of every data point with the i^{th} cluster and w be the fuzziness factor, which is any real number must be greater than 1($1 \le w \le \infty$). All the Features are extracted from the image data to get the matrix occurrence. Some of the vital features for segmentation have been listed as follows:

Entropy: Necrosis region is segmented based on entropy feature. This provides the amount of information related to the original images required for image compression and segmentation, which calculate the Region of interest (ROI) and dissimilarity in ROI and measure randomness. The accurate prediction of necrosis region is obtained by applying entropy feature.

The entropy (C_E) is calculated as follows:

$$C_E = -\sum_{i=1}^{\max\ row} \sum_{j=1}^{\max\ col} R_I(i, j) \log\ R_I(i, j) \tag{7}$$

Contrast: The edema region is segmented based on contrast feature. Contrast is a measure of pixel intensity and its neighbor over the image. Edema region is darker than the surrounding region hence, we choose contrast feature for edema. It is defined as,

$$C_n = \sum_{i=1}^{\max\ row} \sum_{j=1}^{\max\ col} (i - j)^2 \sum_{i=1}^{\max\ row} \sum_{j=1}^{\max\ col} R_I(i, j) \tag{8}$$

Mean: It measure the average of the intensity value to determine the enhanced tumor region. This is calculated as follows;

$$\text{Mean} = \sum_{i=1}^{\max\ row} \sum_{j=1}^{\max\ col} (i, j) \times R_{I\, i, j} \tag{9}$$

Steps for CS-FCM Algorithm:

The input to this algorithm is the m pixel value in an image and w be the fuzziness value. In this, we use the fuzziness value will be 2.

Step 1: Read region of interest (ROI) image.

Step 2: Initialize the number of cluster center u_j, number of cluster c and w>1.

Step 3: Calculate the distance using chi-square, then

$$s_{ij} = \sqrt{\sum_{i=1}^{m} \frac{x_i - u_j}{x_i + u_j}} \tag{10}$$

Where, x_i is the ith pixel in image m. u_j be the jth cluster in u.

Step 4: Update the membership function matrix F= $\{F_{ij}\}$ using equation (11),

$$F_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\sqrt{\left(\frac{x_i - u_j}{x_i + u_j} \right)^2}}{\sqrt{\left(\frac{x_i - u_k}{x_i + u_k} \right)^2}} \right)^{\frac{2}{m-1}}} \tag{11}$$

Step 5: Update the cluster center u=$\{u_j\}$ using equation (12)

$$u_j = \frac{\sum_{j=1}^{m} F_{ij}^{\ w} \times x_i}{\sum_{j=1}^{m} F_{ij}^{\ w}} \tag{12}$$

Step 6: Calculate the fuzzy membership

Where, 't' be the number of iteration steps, ε is the termination criteria and constant term between 0 and 1.The process will stop when $\max_{ij}\left\{\left|F_{ij}^{\ t+1} - F_{ij}^{\ t}\right|\right\} < \varepsilon$ is attained, else go to step 3.

This approaches segment the tumor based on chi-square FCM algorithm with high accuracy and enhance the tumor segmentation in MRI images.

4 EXPERIMENTAL RESULT

Experiment can be performed on the basis of the image provided by the BRATS 2015 dataset on a computing server with intel E5-2620 CPU's and multiple Tesla K80 GPU's. MATLAB R2017a is used to simulate this experiment. Here, we use MRI Brain images for every patient under different modality, namely, T1, T1c, T2, and FLAIR from BRATS benchmark dataset. This dataset comprises 274 MRI images for training and 110 for testing. Analysis can be carried out using the testing data. Here, we partition the entire dataset into two groups, i.e., high grade glioma images and low grade glioma images. And then tumor is segmented into three parts, namely, necrotic core, edema and enhanced tumor. Performance metrics can be calculated using Jaccard matching, specificity, PPV and dice similarity coefficient. BRATS 2015 evaluation metrics for tumor segmentation using FCM clustering for necrotic core, edema and enhanced tumor are Jaccard matching, specificity, PPV and dice similarity coefficient. The performance metrics for tumor segmentation via clustering are defined as follows,

Dice similarity coefficient (DSC)

In Brain tumor Segmentation via clustering, DSC is a familiar similarity index. In this method, we get the binary map for the segmented tumor region $S_1 \in [0,1]$ with the ground truth $T_1 \in [0,1]$. DSC estimate the overlapped region between the ground truth and segmented image. It is described as follows,

$$D_s = \frac{(S_1 \cap T_1)}{\frac{(|S_1| + |T_1|)}{2}} \tag{12}$$

D_s be the dice similarity coefficient, S_1 represents the segmented image and T_1 is the ground truth image.

Jaccard index:

It measure the similarity between the segmented image and ground truth image. Higher value of the Jaccard index shows a better outcome i.e.) similarity between two object is more.

$$J_I = \frac{|S_1 \cap T_1|}{|S_1 \cup T_1|} \tag{13}$$

Here, J_I represents the Jaccard index, T_1 is the ground truth image and S_1 is the segmented image.

Positive predictive value

PPV is defined at which the result is obtained as positive there is a high possibility of disease is presence.

$$\mathrm{P_v} = \frac{|\mathrm{S}_1 \cap T_1|}{|S_1|} \tag{14}$$

Sensitivity (TPR)

Sensitivity is otherwise known true positive rate, which compute the fraction of positive that are correctly identified.

$$\mathrm{S_v} = \frac{|\mathrm{S}_1 \cap T_1|}{|T_1|} \tag{15}$$

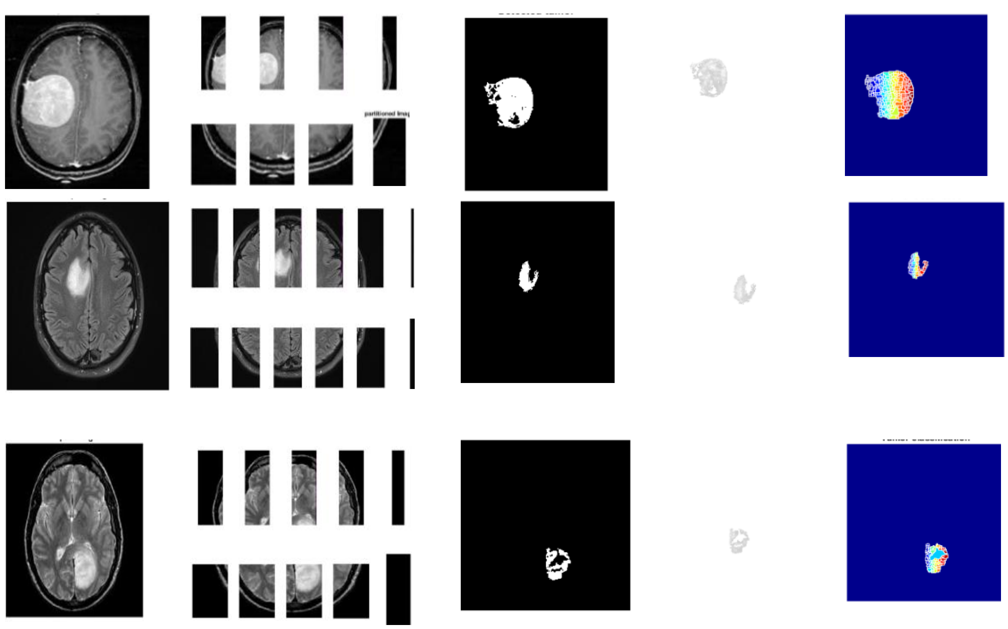
Table 1: *Comparison between our proposed method with other state of art method using BRATS 2015 dataset*

Methods	DSC	PPV	Sensitivity (TPR)	Jaccard index
FCNN+CRF [12]	0.80	0.82	0.81	-
SDAE [13]	0.90	-	-	0.83
parameter free clustering [14]	0.75	-	-	-
3D DEEP LEARNING [15]	0.89	0.92	0.94	0.80
CFCN+CRF[17]	0.86	-	0.91	-
Proposed	0.93	0.91	0.92	0.91

Table 2: *Segmentation via clustering result for BRATS 2015 Dataset*

Method	Proposed
Positive predictive value (PPV)	0.91
Sensitivity(TPR)	0.92
Dice index	0.93
Jaccard index	0.91
Accuracy	0.93

We determine the segmentation via clustering result by using the metrics Jaccard matching, specificity, PPV and DSC. The location for edema, necrosis and enhanced tumor are almost similar.so, segmentation is very difficult by using various methods. But our proposed approach is used to cluster these three region based on the evaluation metrics. Moreover there is still have some fault amongst the segmented result and ground truth, finally segmentation result is very close to the ground truth. Table 2 depict the experimental result for clustering the tumor based on edema, necrosis and enhanced tumor using BRATS 2015 dataset, which includes Jaccard matching, specificity, PPV and DSC.



a) b) c) d) e)

Fig.2: Output result obtained with the three collected input MRI images obtained from the BRATS 2015 dataset a) Input Image, b) Partitioned Image, c) Detected tumor, d) ROI extraction and e) Classified tumor

Fig. 2 show the output result of the proposed technique obtained by the three sample input MRI images. Initially, partitioning is performed and then the tumor region is detected from the input MRI image by means of CS-LBP method. Finally, chi-square based FCM clustering method is used to segment the region into edema, necrosis core and enhancing tumor regions.

In ref [11] presented a CRF-RNN based novel approach, which degrade the performance of tumor segmentation. In our method, we introduce a clustering based approach to enhance the performance of segmentation. Our method attains better performance than SDAEs in terms of accurate segmentation. In the parameter free clustering approach, produce low dice index value when comparing with other approaches. 3D Deep Learning is the second topmost segmentation approach than other existing methods but its performance is low while comparing to the proposed method. Moreover comparison are made with other method for our proposed method in terms of segmentation via clustering show the better segmentation and accuracy. Table 1 depicts the comparison of our proposed method with other state of art methods show segmentation via clustering is achieved with better outcome in the multi-modality images.

5 CONCLUSION

In this work, we introduced a novel clustering based segmentation of MRI image. In the first step is preprocessing is applied to extricate ROI based adaptive thresholding with CS-LBP feature. Once we extract the ROI, we use chi square distance based FCM to cluster the image with respect to edema, necrosis and enhanced tumor region using the feature. Segmentation via chi square distance based FCM can segment the brain tumor predictively than other existing methods. Experimentation can be carried out using BRATS 2015 dataset. Performance metrics for this proposed method achieve better in terms of Jaccard matching, specificity, PPV, and dice similarity coefficient.

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