

Modified Kernel Based Fuzzy Clustering for MR Brain Image Segmentation using Deep Learning

Kalyanapu Srinivas, B. R. S. Reddy



Abstract: *The segmentation procedure might cause error in diagnosing MR images due to the artifacts and noises that exist in it. This may lead to misclassifying normal tissue as abnormal tissue. In addition, it is also required to model the ontogenesis of a tumour, as they propagate at distinctive rates in contrast to their surroundings. Hence, it is still a challenging task to segment MR brain images due to possible noise presence, bias field and impact of partial volume. This article presents an efficient approach for segmenting MR brain images using a modified kernel based fuzzy clustering (MKFC) algorithm. In addition, this approach computes the weight of each picture element based on the local mutation coefficient (LMC). The proposed system would reflexively group normal tissues like white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF) respectively, from abnormal tissue, such as a tumour region, in MR brain images. Simulation outcomes have shown that the performance of the proposed segmentation approach is superior to the existing segmentation algorithms in terms of both ocular and quantitative analysis.*

Keywords : *MR brain image, tumour, data clustering, image segmentation, fuzzy-c means algorithm, gaussian kernel, deep learning convolutional neural networks.*

I. INTRODUCTION

Image segmentation is an important and extensive way of appropriately classifying the pixel values of an image in decision-oriented applications. It partitions an image into even and non-overlapping areas, depending on some similarity measure. It is one of the most challenging tasks in image processing, and a very important pre-processing step in the fields of computer vision, image analysis, pattern recognition, medical image processing, remote sensing, and geographical information systems [1]. It is broadly used by customer display schemes to improve the eminence of image processing techniques, and has two elementary image properties: 1) intensity values comprised of discontinuity that denotes immediate or unexpected variations in intensity as boundaries, and 2) similarity that segregates a digital image

into areas according to some pre-specified similarity principle. It plays a vital role in the field of medical applications, since medical images are a significant part of objective diagnosis that assists in analytic thinking and inferring. The methodology is to build an inner representation of a person's body for objective medical intentions. Medical images are obtained by using different modalities, including X-ray, computed tomography (CT), positron emission tomography and magnetic resonance imaging (MRI). When analyzing the MR brain images, it is essential to determine suitable medical care for abnormal alterations in tissues and organs, which is cited as segmentation. However, segmentation of these sorts of images becomes difficult due to factors like obscure noise, impact of overtone volume, and irregularity of intensity. In the literature, many algorithms have been implemented and published for medical image segmentation. Image segmentation is classified into several categories based on the nature of their specific application, since it is a primary processing stage in many real-time applications. Clustering is an algorithm that groups a number of similar kinds of components or colors into numerous clusters by relying on gray and color intensity resemblance. The major motive for clustering a medical image is to extract prevalent colors from it. Segmentation or clustering significantly simplifies the extraction of color, structure, shape and texture information. These clustering approaches are widely categorized into two groups: hierarchical and partitional clustering [2, 3]. The first category renders a hierarchical cluster tree, referred to as a dendrogram, that might be either divisive or agglomerative [2]. The second category contributes a unitary partition of objects by a pre-specified number of clusters. Among partitional clustering approaches, fuzzy c-means (FCM) is a well-known and very popular scheme [3] and [4], which segments an image into several partitions based on the membership function, which is utilized to distinguish closely related picture elements in an image with positive and negative membership values.

Afterwards, many alterations have been made to the basic FCM clustering [5-8]. Though it produces accurate outcome of segmentation, it requires higher computational time to segment an image, as it relies on the value of membership function for each picture element. Practically, the incertitude in medical images happens in conditions of fuzziness in inaccurate gray levels and boundary of objects. In general, faltering originates when setting the function of membership because of incertitude existence in gray levels.

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Regrettably, traditional clustering of FCM has failed to deal with this faltering. To manage this faltering, Xu et al. implemented a set of fuzzy with higher orders, referred to as the intuitionistic fuzzy set (IFS) [8]. IFS consider both membership (μ) and non-membership (ν) values and the degree of non-membership is lesser or equal to the membership degree complement where the same is adequate in the classical set of fuzzy; this is because of the intuitionism index or the degree of faltering. Further, a review of a wide range of FCM clustering techniques is addressed in [9]. The author in [10] presented an FCM clustering approach that employs the membership function values based on the probability. Recently, Kumar et al. implemented a novel FCM clustering for medical image segmentation, which operates based on weighted spatial kernel that produces spatial information to eliminate uncertainty in finding the exact location in the medical images [11]. Recently, an efficacious framework to identify and cluster the tumour part from MR brain image is presented in [17], where the authors implemented wrapping-based curvelet transform (CT) for denoising and modified spatial FCM algorithm [18, 19]. However, this technique is unable to keep up with the details of fine scale at lower noise strength and it is difficult to sample on a rectangular grid since CT was developed in continuous domain and directions other than horizontal and vertical are very different on a rectangular grid. Further, the membership matrix was initiated randomly. Anupama et al. proposed an efficient clustering, named as generalized rough intuitionistic FCM, which obviates habituation of fuzzy membership function [20]. It was free from the habituation of parameters and membership function. Rajesh et al. implemented a rough set theory and particle swarm optimization neural network (PSO-NN)-based tumour detection and classification in MR brain images, where extraction of features is done by employing rough set theory and tumour classification was obtained with PSO-NN [21]. Later, a low-power architecture is presented for MR brain image segmentation by employing convolutional neural networks (CNN) [22]. Recently, Kalyanapu et al. presented unified iterative partitioned FCM approach for segmenting MR brain images with multiple tumors [26]. But classification wasn't considered in this article for finding tumor classification. Further, authors didn't assume the segmentation of normal MR brain images. However, the segmentation methods in the literature failed to deal with tumor classification and accurate tissue detection. Therefore, this article implements a new framework for segmentation of medical images with better accuracy over several segmentation approaches discussed previously.

The rest of this paper is organized as follows: Section 2 describes the background of FCM clustering algorithm. Our proposed segmentation framework is explained in section 3. Section 4 describes the results and discussion of proposed and conventional medical image segmentation approaches with clinical MR images. Finally, conclusions and future work are presented in section 5 followed by the references.

II. FUZZY C MEANS CLUSTERING

Initially, FCM was implemented by J.C. Dunn in 1973 and later it was enhanced by J.C. Bezdek in 1981. It is quite like

that of another clustering approach, named K-means:

- First, select the cluster quantity.
- Now, allocate random coefficients to every picture element in an image in the clusters.
- Iterate the procedure till the convergence obtained, i.e. the difference between a couple of iterations is not more than the value of the assigned sensitivity threshold.
- Calculate the centroid for each cluster.
- Calculate their coefficients for every picture element in an image in the cluster.

A. Algorithm

Regarding the provided criterion, FCM is employed to partition a finite accumulation of n elements $X = \{x_1, x_2, \dots, x_n\}$ into $v = \{v_1, v_2, \dots, v_c\}$ fuzzy clusters accumulation. For a given finite set of information, FCM returns v and a matrix of partition $W = w_{ij} \in [0,1], i = 1, 2, \dots, n$ for every w_{ij} element, and evidence for the degree to which element x_i is adjunct to the cluster k_j .

The FCM aims to understate following function:

$$\arg \min_x \sum_{i=1}^n \sum_{j=1}^c w_{ij}^m \|x_i - v_j\|^2 \quad (1)$$

Where

$$w_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{\|x_i - v_j\|}{\|x_i - v_k\|} \right)^{2/m-1}} \quad (2)$$

$$v_j = \frac{\sum_{i=1}^n w_{ij}^m x_i}{\sum_{i=1}^n w_{ij}^m} \quad (3)$$

Clustering with K-means also aims to minimize the objective function given in eq. (1). FCM dissents from the objective function of K-means by the membership values w_{ij} summation and the fuzzifier $m \in \mathbb{R}$ with $m \geq 1$, which decides the cluster fuzziness level. Improvements in m led to tiny w_{ij} values and, thus, fuzzier clusters in the limit of $m = 1$, w_{ij} converge to 0 or 1, which results in a crisp partitioning. Ideally, the value of m is fixed to 2 in the domain knowledge absence. Then FCM understates the variance of intra-cluster as well but has similar issues as K-means; the minimum is a local minimum, and the outcome relies on the initial weight's selection.

Therefore, further enhancement is required to set the cluster quantity adaptively that will upgrade the segmentation performance of FCM clustering approach [4]. The traditional FCM clustering discussed above is quite sensitive to noise as the objective function in eq. (1) does not contain any local info. Further, in the presence of noise, the segmentation accuracy will also be mitigated.

To defeat this issue, Ahmed et al. [12] added a term for the adjacent pixel's spatial information to the objective function as given below:

$$J_{M-FCM} = \sum_{i=1}^n \sum_{j=1}^c w_{ij}^m \|x_i - v_j\|^2 + \frac{\beta}{N_w} \sum_{i=1}^n \sum_{j=1}^c w_{ij}^m \left(\sum_{r \in N_i} \|x_r - v_j\|^2 \right)$$

(4)



Where adjacent picture elements spatial info is controlled by the parameter β ($0 < \beta \leq 1$), a set of picture elements close to pixel i is denoted as N_i and N_R is the quantity of N_i .

However, this approach is computationally expensive as the local adjacent term has to be computed in every stage of iteration, which is later overcome by Chen and Zhang [13] by replacing the term $1/N_R \sum_{r \in N_i} \|x_r - v_j\|^2$ in eq. (4) with the $\|\bar{x}_i - v_j\|^2$, where \bar{x} is the filtered image grayscale that could be computed once in advance, and employed a function of kernel to substitute the traditional Euclidean distance. The improvement could be in two forms i.e. either by adopting an average filter or by employing a median filter. Their objective function is as follows:

$$J_{FCM_{A,M}} = \sum_{i=1}^n \sum_{j=1}^c w_{ij}^m \|x_i - v_j\|^2 + \beta \sum_{i=1}^n \sum_{j=1}^c w_{ij}^m \|\bar{x}_i - v_j\|^2 \quad (5)$$

Although there is an enhancement in the segmentation accuracy, this approach is sensitive to several kinds of noise of higher levels. In summation, β value is set manually with concern to noise and needs anterior info regarding noise.

To handle the adjusting of parameter issue, author in [14] presented an algorithm that relies on FLICM by a factor of fuzzy, which unified the contiguous picture elements' spatial and grayscale info. Although FLICM algorithm enhances robustness to noise and artifacts, it is slow since the fuzzy factor must be calculated in each iteration. In addition, this is intemperately influenced with the spatial Euclidean distance from the cardinal picture component to its contiguous pixels to miss tiny details in images because of the impact of smoothing.

Later, an improvement for FLICM was implemented by Gong et al. [15], where the KWFLICM framework was designed with a trade-off leaden component of fuzzy to operate the relationship of local adjacent and repositioned the traditional distance with kernel operation. This trade-off leaden element of fuzzy unifies the local spatial and grayscale info [15]. Due to this element, there is a significant enhancement in the computational worth. Moreover, small image details haven't upheld in this approach.

To this end, a refresh path to alter the subsisting FCM clustering is researched by adaptive regulation for contextual information. In this article, a novel model is implemented, which controls the impact of the picture element adjacent depending on LMC. Further, a weighted image is formulated, which unifies the local contextual info concerning the LMC and the NLEM filtered grayscale in non-subsampled space that is computed earlier to mitigate the computational price. Moreover, a gaussian kernel is applied to enhance the accuracy of segmentation and hardness to outliers.

III. PROPOSED METHODOLOGY

This section explains the proposed segmentation framework for medical images. In general, parameter β employed in conventional FCM approaches (discussed in section 2) is set in advance to assure the suitable contextual info quantity. In truth, the level of noise alters from one window to another, so, invariable β for each pixel is not suitable. Further, it requires anterior knowledge regarding

noise that is almost impossible in real-time nature. Thus, adaptive computation of β is essential concurring to the picture element being processed.

A. Computation of Weights

Weights of each pixel is computed by employing the LMC, which is referred as a ratio of local variance of each pixel (L_{var_i}) to the local average of each pixel (L_{avg_i}). The average filtering with local window is utilized to calculate L_{avg_i} and L_{var_i} is attained by applying the standard deviation filtering to the input image. Then the LMC is defined as follows:

$$LMC_i = \frac{L_{var_i}}{L_{avg_i}^2} \quad (11)$$

Now, exponential function, \mathcal{E}_i is employed for LMC_i and local accumulation of LMC_i to compute the weights, w_i in each picture element. Further, an inflexion parameter ϕ_i , is utilized to assign weights to every picture element as follows:

$$\phi_i = \begin{cases} \xi + w_i, & L_{avg_i} > x_i \\ \xi - w_i, & L_{avg_i} < x_i \\ 0, & L_{avg_i} = x_i \end{cases} \quad (12)$$

For the pixels with larger L_{avg_i} , the parameter ϕ_i assigns higher values. When L_{avg_i} is equal to x_i then ϕ_i will be zero, which behaves like the traditional FCM clustering algorithm. ξ denote the positive constant probably 2 that trade-off the rate of convergence and capacity to hold back the details. In eq. (5), parameter β is replaced with the inflexion parameter expressed in eq. (12).

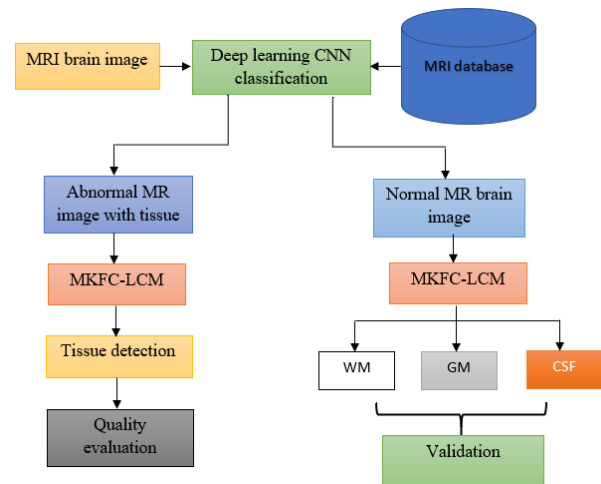


Fig. 1. Proposed framework for MRI brain image segmentation

Algorithm 1: MKFC-LMC

Step 1: Initialize the parameters $v, w^{(0)}, t = 0$ and $m = 2$

Step 2: Select and read an MR brain image which is to be segmented

Step 3: Compute weights of every picture element by employing LMC_i as expressed in eq. (11)

Step 4: Compute the inflexion parameter ϕ_i , as mentioned in eq. (12)

Step 5: Using eq. (13), compute the modified kernel based on gaussian function.

Step 6: Finally, compute the number of clusters centres and new membership function values.

Step 7: Evaluate the obtained segmented outcome using quality metrics like Jaccard index and running time.

B. Modified Kernel Function

In practice, measurement of distance is computed by the Euclidean distance metric due to its simplicity and inexpensiveness. But it is tender to fluster and outliers. To address this, kernel functions are implemented in recent days, which are capable to externalize the information into a space of high dimension where the info could be differentiated to greater extent. To obtain this, kernel function is assumed to map a linear algorithm into no-linear one by employing a dot multiplication. The kernel width is computed as,

$$\sigma = \sqrt{\frac{\sum_{i=1}^N (d_i - \bar{d})^2}{N-1}} \quad (13)$$

Where, d_i denotes that the absolute distance values from each pixel i to the average of all pixels and mean of all distances is denoted as \bar{d} .

C. Convolution Neural Networks (CNNs)

Convolutional Neural Network (CNN) is widely used in field of image processing. CNN is inspired by means of biological processes, such as the human brain can distinguish between different objects by just visualizing, with the help of previous observations. This phenomenon can be widely used in bio medical image processing, to classify different images and detect the disease [23-25]. This requires a large dataset to train the CNN system to classify the image properly. The images also have to be processed before inputting to the CNN system to establish better diagnosis of the disease. Image pre-processing can be accelerated by means of hardware and then applying the test image to the CNN system. This paper concentrates on realizing tissue rendering, which is one of the major steps in image processing that accelerates the disease diagnosis.

IV. RESULTS AND DISCUSSION

The experimental analysis of proposed segmentation framework carried out in three stages. In the primary stage, normal MR brain images are considered and segmented into WM, GM and CSF respectively with an accurate detection over existing segmentation algorithms. Further, qualitative performance also provided to show the effectiveness of proposed MKFC-LCM algorithm. In the second stage, abnormal MR brain images are assumed with single tumors and separated the tumour part with good enough accuracy over existing segmentation algorithms. Further, it has also computed the area or size of the detected tumour for post simulation process. At last, it is considered the abnormal MR brain images with multiple tumors and detected those tumors.

The performance quality metrics also computed to disclose the superiority of proposed MKFC-LCM approach over existing segmentation algorithms.

A. Stage 1: Normal MR brain images

This section describes the experimental analysis of proposed segmentation framework with comparison to the conventional segmentation approaches. Simulated Brain Database (SBD) [16] is considered for testing the proposed medical image segmentation approach, where the SBD comprises a realistic MR volume set generated by an MR imaging simulator with their ground truths of WM, GM and CSF available. Fig. 2 disclose that the segmentation of T1-weighted axial slice (number 100) with 217×181 pixels corrupted with the noise of 7% and grayscale nonuniformity of 20% into WM, GM, and CSF, where the proposed segmentation method obtained a better separation of WM, GM and CSF as compared to the approaches presented in literature like classical FCM [4], Ahmed et al. [12], and Gong et al. [15]. The running time and Jaccard index values are demonstrated in Table 1. As given in Table 1, besides classical FCM, proposed framework consumes less running time over the other segmentation approaches presented in literature.

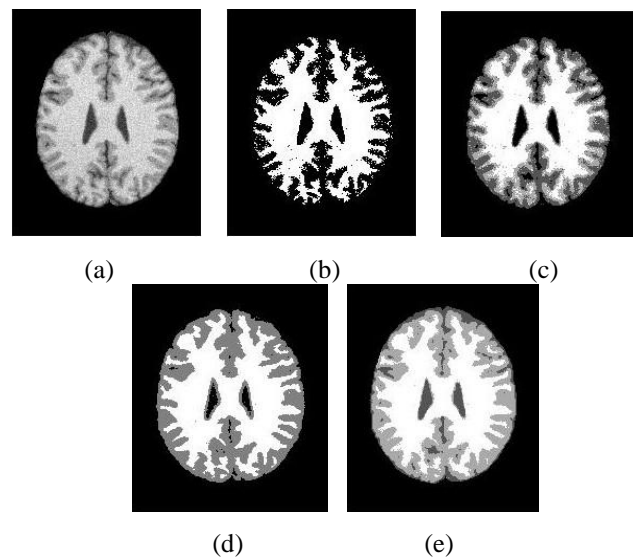


Fig. 2. Segmented outcome of T1-weighted axial slice (number 100) from SBD with 7% noise and 20% grayscale nonuniformity (a) original image (b) classical FCM [4] (c) Ahmed et al. [12] (d) Gong et al. [15] (e) MKFC-LCM

Table 1. Obtained quality metric values with the proposed and existing segmentation approaches for Fig. 5

Parameter	Classical FCM [4]	Ahmed et al. [12]	Gong et al. [15]	MKFC-LCM
Jaccard index	0.59	0.79	0.865	0.94
Execution time (in sec)	14.58	10.59	139.47	3.18

1) Jaccard Index

Jaccard index (JI) is a similarity measure which is known as Jaccard similarity coefficient.

It's very popular and frequently used as similarity indices for binary data. The area of overlap A_i is calculated between the segmented image B_i and its corresponding ground truth image G_i as shown in equation

$$Jaccard\ Index\ (A_i) = \frac{|B_i \cap G_i|}{|B_i \cup G_i|} \times 100 \quad (14)$$

If the segmented object and corresponding ground truth image G_i are exactly similar then the measure is 100 and measure 0 represents they are totally dissimilar, however the higher the measure indicates more similarity.

B. Stage 2: Abnormal MR brain images with single tumour

Fig. 3 demonstrated that the considered MR brain images with single tumour. Segmented results obtained from various approaches like classical FCM [4], Ahmed et al. [12], Gong et al. [15] and proposed MKFC-LCM algorithm is presented in fig. 4, where the outcome of segmentation is quite accurate with the MKFC-LCM over the existing fuzzy clustering-based segmentation approaches.

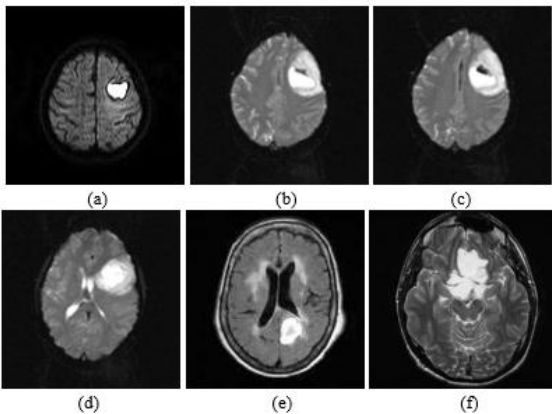


Fig. 3. Abnormal brain images data set with single tissue

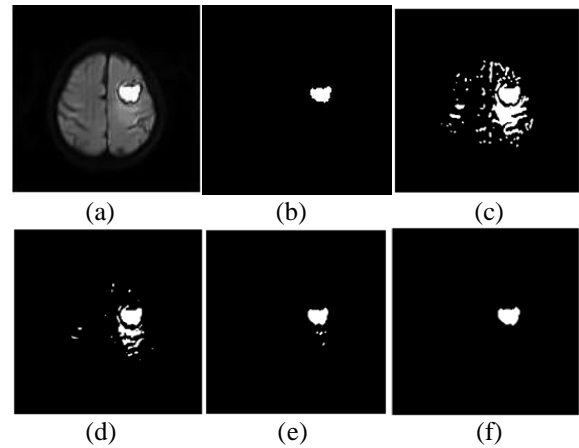


Fig. 4. Segmented outcome of abnormal brain image with tissue (a) Original MR brain image (b) ground truth image (c) classical FCM [4] (d) Ahmed et al. [12] (e) Gong et al. [15] (f) MKFC-LCM

Table 2. Obtained tumour area values using binarization approach for Fig. 4

Clustered algorithm	Area of the tumour (mm ²)					
	Image a	Image b	Image c	Image d	Image e	Image f
Classical FCM [4]	8.8035	18.3038	18.8829	19.6782	12.025	22.6656
Ahmed et al. [12]	13.6746	13.5954	13.4899	13.1497	13.65	18.9235
Gong et al. [15]	6.1291	13.7077	13.5363	13.2053	8.89	19.0721
MKFC-LCM	6.1462	12.1898	12.3602	11.6758	8.74	14.0442

1) Binarization

Binarization is used to calculate the tumour area and the obtained values of different clustering algorithms are demonstrated in Table 2. In this, abnormal MR brain images are assumed with a size of 256 × 256 and the obtained outcome of segmentation consists just couple of picture element values i.e., one is black and the other is white, where black and white denotes that the value of pixel is 0 and 1 respectively. Therefore, the segmented outcome is defined as a total sum of black and white pixels.

$$M = \sum_{x=1}^L \sum_{y=1}^L [f_{x,y}(0) + f_{x,y}(1)],$$

where $L = 1, 2, 3 \dots 256$

$f_{x,y}(0)$ = black pixel having the value of zero,

$f_{x,y}(1)$ = white pixels having the value of one

$$P = \sum_{i=1}^L \sum_{j=1}^L f_{x,y}(1) \quad (15)$$

Where, P = number of white pixels

Now, by using the above equation, we can calculate the area of the segmented tumour based on the typography and digital imaging units, where one pixel is equal to 0.264583 millimeter. i.e., 1 pixel = 0.264583 mm

Then the area of tumour can be expressed as follows:

$$A_{Tumor} = (\sqrt{P}) \times 0.264mm^2 \quad (16)$$

2) Accuracy

This is utilized to assess the similarities between the images of segmented result

and the GT. It is formulated by employing four arguments. Those are:

- False Positive (FP): Genuine pixel count in GT image those are not existed in the area of segmentation.
- True Positive (TP): Count of GT image's true pixels accurately recognized as the pixels of segmentation.
- True Negative (TN): The false pixel count in GT image exactly identified as the pixels of segmentation.
- False Negative (FN): Count of GT image's false pixels accurately recognized as the pixels of segmentation.

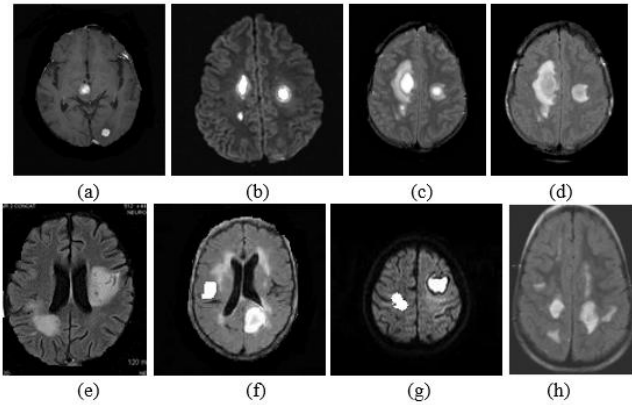


Fig. 5. Abnormal brain images data set with multiple tissue

C. Stage 3: Abnormal MR brain images with multiple tumors

Fig. 5 demonstrated that the abnormal MR brain images with multiple tumors. For testing purpose, we considered Fig. 6(f) and the outcome of segmentation obtained from various approaches classical FCM [4], Ahmed et al. [12], Gong et al. [15] and proposed MKFC-LCM algorithm is presented in fig.

6. It is observed that the segmented results of existing algorithms presented additional WM where the outcome of segmentation is quite accurate with the MKFC-LCM over the existing fuzzy clustering-based segmentation approaches. Table 3 discloses the quality parameters obtained for segmented outcome of Fig. 6, where it computes sensitivity, accuracy and running time. Further, it also calculated the size of tumour 1 and tumour 2 separately.

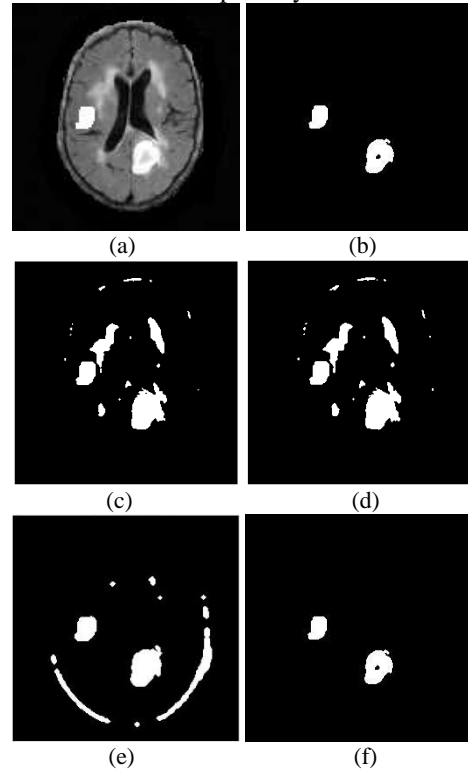


Fig. 6. Segmented outcome of abnormal brain image with multi tissues (a) pre-processed using proposed denoising method (b) ground truth image (c) classical FCM [4] (d) Ahmed et al. [12] (e) Gong et al. [15] (f) MKFC-LCM

Table 3. Performance metrics of various segmentation algorithms for abnormal MR brain images with multiple tumors

Parameter	Algorithm			
	Classical FCM [4]	Ahmed et al. [12]	Gong et al. [15]	MKFC-LCM
Sensitivity (in %)	55.63	58.15	78.98	93.22
Accuracy (in %)	96.13	96.33	97.05	98.43
Running time (in sec)	8.92	8.15	7.45	4.18
Size of tumour 1 (in mm ²)	9.3	9.54	6.98	5.51
Size of tumour 2 (in mm ²)	11.55	11.8	9.99	7.86

V. RESULTS AND DISCUSSION

This article presented a modified kernel based fuzzy clustering approach for MR brain image segmentation using deep learning convolutional neural networks. Further, proposed segmentation algorithm computes the weight of each picture element based on local mutation coefficient (LMC). The main concentration of this approach is to segment normal MR brain images as WM, GM and CSF and abnormal MR image as separated tumour part automatically. Experimental analysis disclosed that the proposed segmentation approach with CNN performed quite superior to the existing segmentation algorithms in terms of both ocular and quantitative analysis.

REFERENCES

1. N. R. Pal and S. K. Pal, "A review on image segmentation techniques", Pattern Recognition, vol. 26, no. 9, pp. 1277-1294, 1993.
2. R. Zennouhi, L. Masmoudi and M. E. Ansari, "Image segmentation using hierarchal analysis of 2D histograms- Applications to medical images", In Proc. of International Conference on Multimedia Computing and Systems, Morocco, Apr. 2009.
3. H. P. Ng, S. H. Ong, K. W. C. Foong, P. S. Goh and W. L. Nowinski, "Medical image segmentation using k-means and improved watershed algorithm", In Proc. of Southwest Symposium on Image Analysis and Interpretation, Denver, USA, 2006.
4. M. C. Clark, L. O. Hall, D. B. Goldgof, L. P. Clarke, R. P. Velthuizen and M. S. Silbiger, "MRI segmentation using fuzzy clustering techniques", IEEE Engineering in Medicine and Biology Magazine, vol. 13, no. 5, pp. 730-742, 1994.
5. D. L. Pham and J. L. Prince, "Adaptive fuzzy segmentation of magnetic resonance images", IEEE



6. N. A. Mohammad, M. N. Ahmed and A. Farag, "Modified fuzzy-c means in medical image segmentation", In Proc. of International Conference on Acoustics, Speech and Signal Processing, Phoenix, AZ, USA, Aug. 2002.
7. Y. Yang and S. Huang, "Image segmentation by fuzzy-c means clustering algorithm with a novel penalty term", Computing and Informatics, vol. 26, pp. 17-31, 2007.
8. Z. Xu, J. Chen and J. Wu, "Clustering algorithm for intuitionistic fuzzy sets", Information Science, vol. 178, pp. 3775-3790, 2008.
9. Y. K. Dubey and M. M. Mushrif, "FCM clustering algorithms for segmentation of brain MR images", Advances in Fuzzy Systems, vol. 2016, article ID 3406406.
10. K. Perumal and C. Latha, "Probability based fuzzy-c means for image segmentation", International Journal of Pure and Applied Mathematics, vol. 118, no. 17, pp. 779-789, 2018.
11. S. V. A. Kumar, B. S. Harish and P. Shivakumara, "A novel fuzzy clustering-based system for medical image segmentation", International Journal of Computational Intelligence Studies, vol. 7, no. 1, pp. 33-66, 2018.
12. M. N. Ahmed, S. M. Yamany, N. Mohamed, A. A. Farag, and T. Moriarty, "A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data", IEEE Transactions on Medical Imaging, vol. 21, no. 3, pp. 193-199, 2002.
13. S. Chen and D. Zhang, "Robust image segmentation using FCM with spatial constraints based on new kernel-induced distance measure," IEEE Transactions on Systems, Man, and Cybernetics Part B: Cybernetics, vol. 34, no. 4, pp. 1907-1916, 2004.
14. S. Krinidis and V. Chatzis, "A robust fuzzy local information C-means clustering algorithm," IEEE Transactions on Image Processing, vol. 19, no. 5, pp. 1328-1337, 2010.
15. M. Gong, Y. Liang, J. Shi, W. Ma, and J. Ma, "Fuzzy C-means clustering with local information and kernel metric for image segmentation," IEEE Transactions on Image Processing, vol. 22, no. 2, pp. 573-584, 2013.
16. <http://brainweb.bic.mni.mcgill.ca/brainweb/>
17. Senthilkumar, C. and Gnanamurthy, R.K. Cluster Comput (2018). <https://doi.org/10.1007/s10586-017-1613-x>
18. Liu, J., Li, M., Wang, J., Wu, F., Liu, T., Pan, Y.: A survey of MRI based brain tumour segmentation methods. Tsinghua Sci. Technol. 19(6), pp. 578-595, 2014.
19. Kwak, N., Choi, C.H.: Input feature selection for classification problems. IEEE Trans. Neural Netw. 13(1), pp. 143-159. 2014.
20. Anupama, N., Srinivas Kumar, S. and Srinivasa Reddy, E.: Generalized rough intuitionistic fuzzy c-means for magnetic resonance brain image segmentation. IET Image Process., 11(9), pp. 777-785, 2017.
21. Rajesh, T., Malar, R.S.M. & Geetha, M.R. Cluster Comput (2018). <https://doi.org/10.1007/s10586-018-2111-5>
22. Vardhana, M., Arunkumar, N., Sunitha, L., Enas, A. and Gonzalez, G. R.: Convolutional neural network for biomedical image segmentation with hardware acceleration. Cognitive Sys. Res., 50, pp. 10-14, 2018.
23. Roth, Holger et al.: Deep learning and its application to medical image segmentation. CoRR abs/1803.08691 (2018).
24. Islam, M. T., Aowal, M. A., Minhaz, A. T., and Ashraf, K., "Abnormality detection and localization in chest x-rays using deep convolutional neural networks," arXiv preprint arXiv:1705.09850 (2017).
25. Badrinarayanan, V., Kendall, A., and Cipolla, R., "Segnet: A deepconvolutional encoder-decoder architecture for image segmentation," IEEE Transactions on Pattern Analysis and Machine Intelligence 39(12), pp. 2481-2495, 2017.
26. Kalyanapu Srinivas and Bhaskar Kantapalli, "Segmentation of MR Brain Images Using Unified Iterative Partitioned Fuzzy Clustering", International Journal of Recent Technology and Engineering, vol. 8, no. 1, pp. 2755-2758, May 2019.

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