Brain MRI Segmentation Using Fuzzy Clustering Algorithms

Fatemeh Jamalinabijan* , Ayda Baheri Eslami** , Gülcihan Özdemir***

* Institute of Informatics, Istanbul Technical University, Computer Science, 34469

** Institute of informatics, Istanbul Technical University, Data and Communication Engineering, 34469

*** Institute of informatics, Istanbul Technical University, Computational Science and Engineering, 34469

(nabijan19@itu.edu.tr, eslami20@itu.edu.tr, ozdemirg@itu.edu.tr)

Corresponding Author; Fatemeh Jamalinabijan, Institute of Informatics, Istanbul Technical University, Computer Science, 34469, nabijan19@itu.edu.tr

Received: 15.09.2021 Accepted:29.12.2021

Abstract- On the authority of human realization, the process of partitioning an image into non-overlapping and meaningful parts is called image segmentation. One of the traditional and conventional implementations of image segmentation is Brain MRI segmentation. In most cases, the MRI segmentation procedures are based on clustering approaches and according to the literature studies FCM based algorithms are more noticeable among other methods. Due to some drawbacks of FCM algorithm, like its weak function in the presence of noise, random initial values and easily falling into local optimal solution research have been trying to make some improvements on FCM algorithm. There are plenty of novel FCM based algorithms and In this work, we have implemented two FCM based algorithms (ARKFCM, SFCM2D) with different types of brain MRI images and compared them with conventional FCM to see which one has the better performance on the images with and without noise. Results are shown in the form of segmented images, and they demonstrate that ARK-FCM shows a better performance in keeping the details and being more resistant in working on noisy MRI images**.**

Keywords: Fuzzy, Image segmentation, clustering, Medical images

1. Introduction

Clearly, the foremost aim of image segmentation is dividing an image into different but uniform elements based on some similitude measure for the subsequent analysis. Different applications of image segmentation consist of remote sensing, image analysis, computer vision and medical image processing and autonomous driving.

Among the variety of applications of image segmentation, MRI image segmentation has attracted the attention of researchers due to its importance in medical science. Therefore, in recent years this field has become more imperative.

The methods of Image segmentation can be grouped into different types involving Thresholding, Model-based methods, edge detection, Region growing, and clustering, Neural Network-based approaches, and to name but a few. The most commonly used segmentation procedures depend on clustering approaches. Like segmentation, the aim of clustering is to create groups named clusters and put data with similar traits into them.

In general, clustering has two subgroups named Hard Clustering and Soft clustering Figure. 1 presents the general categories of data clustering. Every data point is a member of one cluster or not in hard clustering. Rather than locating data points in a single cluster, in soft clustering, there is a membership degree with the help of which data points could be assigned into different clusters. Soft clustering is also named fuzzy clustering and allows each data point pertained to be more than a single cluster.

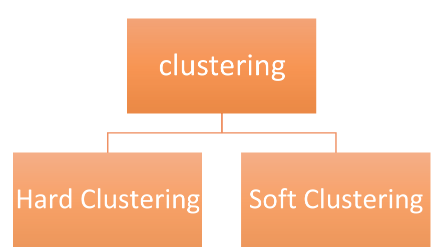

Fig. 1. Clustering Methods

Hard Clustering uses some information like the spatial location of pixels and brightness. It is obvious that this method does not have the capability to divide image regions that have similar pixel intensity by taking into account just their pixel intensity because the pixels of an image is highly correlated with the pixels in their neighbourhood and they have almost the same features most of the times.

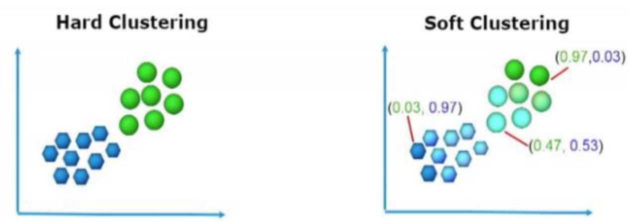

Fig. 2. Clustering methods

Mostly, in real-world applications, there is not any crisp and exact border between clusters. Therefore, fuzzy clustering is most of the time proper for categorization of the data in the decision-based usages such as tumour discovery, tissue classification etc. Classifying the pixel values like exact borders between substances in an image that do not exist, is among one of the most intricate procedures in image analysis. Image segmentation with fuzzy clustering method overcomes this problem by providing a measure of classifying pixel quantities with good accuracy. Figure 3 shows how fuzzy clustering algorithms do segmentation on images.

The privilege of Fuzzy systems is that they can easily be understood and used as the membership function separates the dataset appropriately. Many applications in the literature do not have this property [3].

There are tens of known clustering algorithms, but just a few of them are used significantly. Algorithms like those that are based on Connectivity models and as the name depicts, they work relying on the impression of nearer data points in data space show that they are similar to each other more, compared to the further ones.

Next, algorithms that use Centroid models. They are iterative and the concept of resemblance in them is derived from how much the data point is close to the centre of the cluster. K-means algorithm is a desirable example of this group.

The other well-known algorithms are based on Distribution models that show the probability of happening for all data points in a group have the matching dispersal. Eventually, the last category is based on Density and data space is explored by these models for the varied density of data points.

One of the well-known algorithms in the field of image segmentation is the FCM (Fuzzy C-means) algorithm which follows soft clustering and belongs to the category of centroid models. It has strong specifications for ambivalence and can save information more than hard clustering approaches [3].

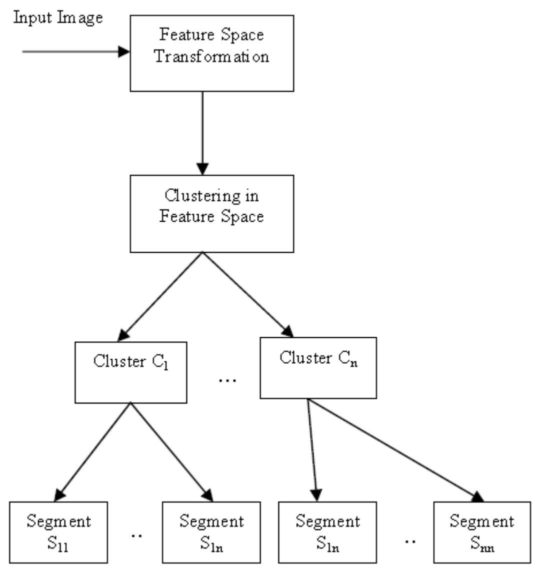

Fig. 3. Steps of Fuzzy Clustering algorithm

The present work focuses on MRI images segmentation based on FCM, and FCM based algorithms. MRI brain images are more commonly used in image segmentation and brain diagnoses.

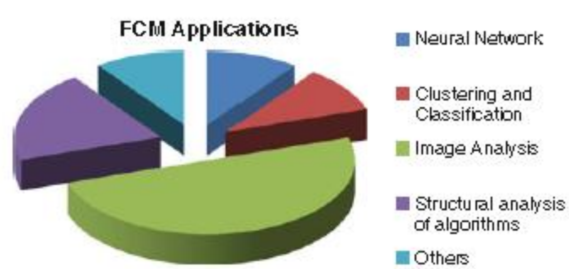

Fig. 4 FCM Applications

FCM was proposed by Dunn [3]. Later Bezdek modified it [10]. In literature, there are several other algorithms that have been proposed to make improvements on classical FCM.

These algorithms are grouped into two subgroups: the first group adds the spatial information to the FCM algorithm [4] and the second group uses a dissimilarity index that eliminates the problem of intensity variation in the objective function in FCM algorithm [3].

1.1 Literature review

[1] Proposed a new meta-heuristics collaboration attitude utilizing the Genetic Algorithm (GA) also Biography based

Algorithm (BBO), and Firefly Algorithm (FA). Empirical outcomes indicate that the proposed method has improved the function of the conventional FCM algorithm.

[2] This study has modified the objective function of the standard FCM with a penalty term that includes the affection of the adjacent pixels on the centre pixel. The performance of the proposed algorithm appears to be effective and robust in comparison with some other derivations of FCM algorithm.

[3] Demonstrates an assessment of contemporary image segmentation methods that use fuzzy clustering algorithms. Four algorithms including Novel fuzzy C-Means (NFCM), Fuzzy Local information C-Means (FLICM), and enhanced Spatial Fuzzy C-Means.

[6] Presents a fast-robust kernel space fuzzy clustering segmentation algorithm by mapping the sample in the space to a feature space with high dimensions through a kernel function. Then current pixel with its neighbour pixels are combined and an image that is linearly weighted filtering is derived. The proposed method separates liver tumours from stomach CT volumes properly.

Clustering is reviewed and compared.

[8] This paper presents a method for image segmentation that is based on Dynamic Particle swarm optimization (DPSO) and conventional FCM algorithm.

DPSO has the advantage to learn the parameters dynamically. The proposed method combines FCM with DPSO while it uses the benefits of global optimization, also includes a system to reduce the noise based on neighbouring pixels.

A modified Fuzzy C-Means clustering algorithm called Gaussian Kernel-Based Fuzzy C-Means clustering algorithm is proposed by [9]. Its main goal is to guarantee noise insensitiveness and preserving image details. It clusters the image with noise from the area with low-intensity in homogeneity.

[10] Is a survey on recent fuzzy c-means algorithms including the Gaussian-Kassel algorithm and the Gath-Geve algorithm and FCM algorithm.

[11] Proposes a novel clustering mechanism based on the fuzzy concept that enhances the unclear MRI/CT scan images before the segmentation. It does some processes before segmentation for minimizing the noise. Then, the computation of lower and upper membership levels for the images is done.

[12] Optimization of fuzzy brainstorm for medical image segmentation is suggested. It is a combination of brainstorm optimization and fuzzy technique.

[4] Has completely explained the mathematical steps of FCM algorithm and tested on Brain MRI images to divide tumors inside the brain into four stages.

[5] Suggests an Adaptively Regularized Kernel-based Fuzzy C-Means clustering framework for segmenting the brain MRI. for the local average grayscale, the structure is formed of three algorithms which are substituted with grayscales.

For an improved medical image segmentation, a novel fuzzy level set algorithm is proposed [7]. It includes spatial information to the classic FCM algorithm.

According to the related works [4], [5], [7] in this study, first, we implemented the ARK-FCM algorithm on the data set of 5 images with different features, which was used in the mentioned work [5]. Then one algorithm which adds spatial information to the FCM, and conventional FCM were implemented using the data set from work [5] and finally, all three algorithms were also tested with another data (image) without any noise and any weighted operation on it.

2 Modelling and Formulation

In this part we explain the algorithms which we have used in our work then we will delve into the steps of this project.

2.1 Fuzzy C-Means (FCM)

The first and main algorithm that we use for segmenting Brain MRI images is FCM algorithm. In the past years, many methods have been developed to improve medical images segmentation with the purpose of accurate diagnosis, but FCM was the most accurate on between other unsupervised learning methods.

Our model passes through some steps as shown in figure 5:

First, the MRI image is imported to the system. Next, the preprocessing process prepares images to be segmented

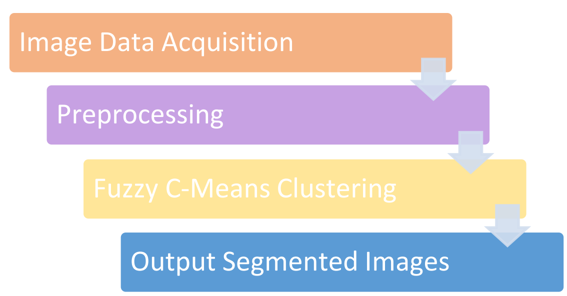

Fig 5. Image segmentation steps using FCM algorithm

Then, the FCM algorithm is implemented and images are segmented. After that, images are converted to the same analogue image as shown in the steps explained below:

2.1.1 FCM algorithm steps:

Basically, FCM method in a mathematical model, which goes through some steps iteratively until it puts all similar data points inside clusters.

Cluster heads can be chosen randomly or using some functions. In this work, we start the first step by choosing random values for cluster heads using the membership matrix. After choosing cluster heads, constraints are calculated for each cluster using the equation:

$$C_j = \frac{\sum_i (\mu_j(X_i))^m X_i}{\sum_i (\mu_j(X_i))^m} \quad (1)$$

Next, the distance (Di) is calculated for each cluster:

$$D_i = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (2)$$

Finally, the membership values are updated.

$$\mu_j(x_i) = \left(\frac{1}{d_{ji}}\right)^{\frac{1}{m-1}} / \sum_{k=1}^{c} \left(\frac{1}{d_{ki}}\right)^{\frac{1}{m-1}} \quad (3)$$

As we already knew FCM does not include spatial information of the pixels and this makes the algorithm sensitive to noise also other artifacts appear.

In addition, since FCM algorithm is based on pixel intensity exclusively, it makes the algorithm sensitive to the variation of intensity in the geometry or illumination of the object.

Furthermore, choosing the cluster heads randomly in the initial step does not seem rational also experiments show that, FCM falls into local optimum solutions easily.

Therefore, we looked for some other FCM based algorithms which overcome these drawbacks and compare them with the conventional FCM.

2.2 *Spatial Fuzzy Clustering algorithm (SFCM)*

This method automates the initial step, choosing and configuration of parameters of the level set segmentation, with a spatial fuzzy level set algorithm. It uses a conventional FCM.

One of the downsides of FCM is that often image noise takes down the proficiency of the algorithm because of the lack of spatial information, so it would be noteworthy to incorporate spatial information into a FCM.

The spatial function is defined as:

$$h_{ij} = \sum_{k \in NB(x_j)} u_{ik}, \quad (4)$$

where NB(xj) represents a square window centred on pixel xj in the spatial domain.

The spatial function is incorporated into the membership function as follows:

$$u'_{ij} = \frac{u_{ij}^p h_{ij}^q}{\sum_{k=1}^{c} u_{kj}^p h_{kj}^q}, \quad (5)$$

Where p and q are parameters to adjust the relative significance of both functions.

2.3 *Adaptively Regularized Kernel-Based Fuzzy C-Means Clustering (ARKFCM)*

This method consists of three steps:

First introduces a parameter for regularizing to enhance segmenting also preserving the detail of the image. The second devises an image that is weighted, and lastly includes the Gaussian radial basis function (GRBF) for higher accuracy.

- Regularizing parameter

The local variation coefficient (LVC) is calculated to approximate the grayscale variance in the local window.

$$\mathrm{LVC}_i = \frac{\sum_{k \in N_i} (x_k - \bar{x}_i)^2}{N_R * (\bar{x}_i)^2}, \quad (6)$$

Then, we apply the LVC to the Exponential function for getting the weighted image:

$$\zeta_i = \exp\left(\sum_{k \in N_i, i \neq k} \mathrm{LVC}_k\right), \quad (7)$$

$$\omega_i = \frac{\zeta_i}{\sum_{k \in N_i} \zeta_k}. \quad (8)$$

every pixel is assigned with an ultimate weight to be related with the local window average grayscale:

(9)

$$\varphi_i = \begin{cases} 2 + \omega_i, & \bar{x}_i < x_i \\ 2 - \omega_i, & \bar{x}_i > x_i \\ 0, & \bar{x}_i = x_i. \end{cases}$$

3 Experimental Results:

In this part implementation results of three algorithms are provided. FCM, SFSM2D, ARKFCM algorithms implemented on different MRI images detailed in table below, also the same implementations are done on MRI image which is without noise and weighted operation on it. Table. 1 presents the data which is used in this works.

Table 1. Dataset and information about data

Name of image	explanation	size
no720_100S	T1-weighted sagittal slice-with 7% noise and 20% Grayscale corruption	[181×217 double]
Brats1	T1-weighted axial slices	[240×240 double]
Brats2	T1-weighted axial slices	[240×240 double]
no720_100A	T1-weighted sagittal slice -with 7% noise and 20% grayscale corruption	[217×181 double]
rice10_91A	T1-weighted axial slice- with 10% Rician noise	[217×181 double]

The results of the implementation are shown in the figures below.

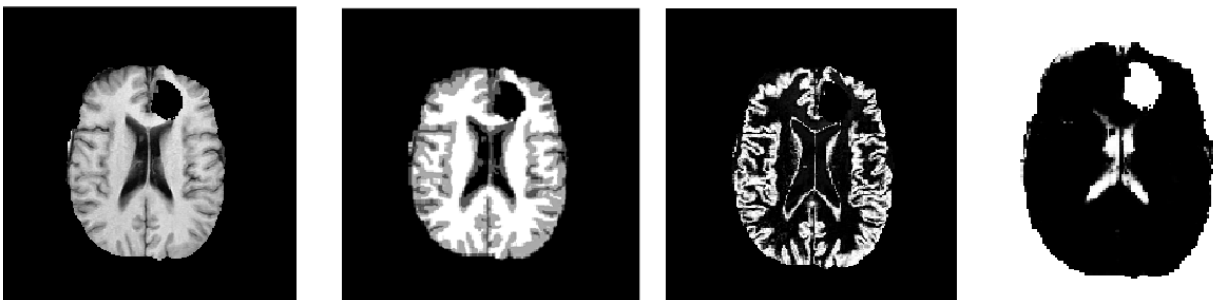

Fig. 6. Comparing of segmentation results for Brats1 image, respectively from left to right: The original image, ARKFCM segmentation result, FCM segmentation result, SFCM2D segmentation result

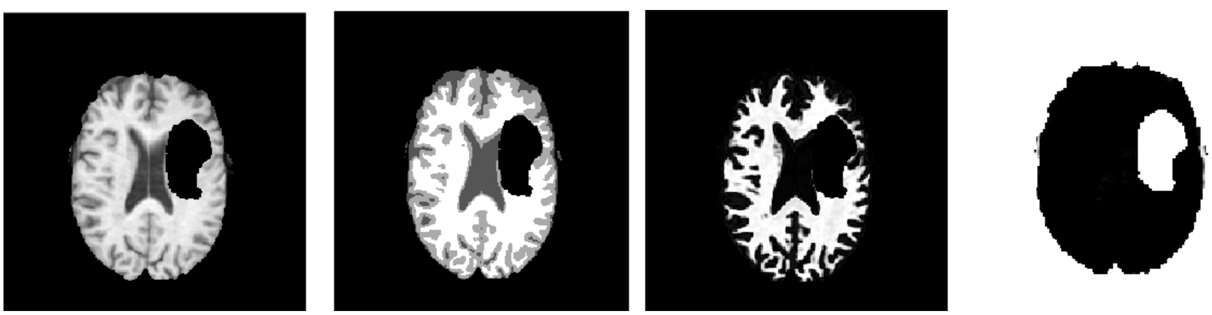

Fig. 7. Comparing of segmentation results for Brats2 image, respectively from left to right: The original image, ARKFCM segmentation result, FCM segmentation result, SFCM2D segmentation result

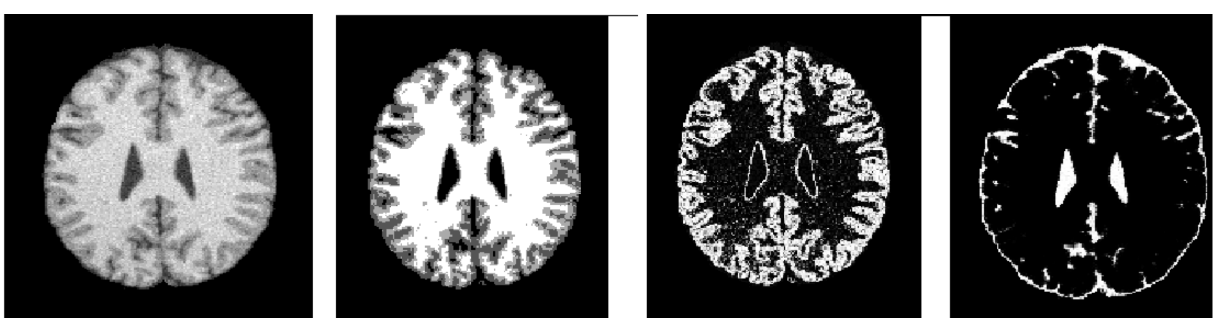

Fig. 8. Comparing of segmentation results for no720_100A image, respectively from left to right: The original image, ARKFCM segmentation result, FCM segmentation result, SFCM2D segmentation result

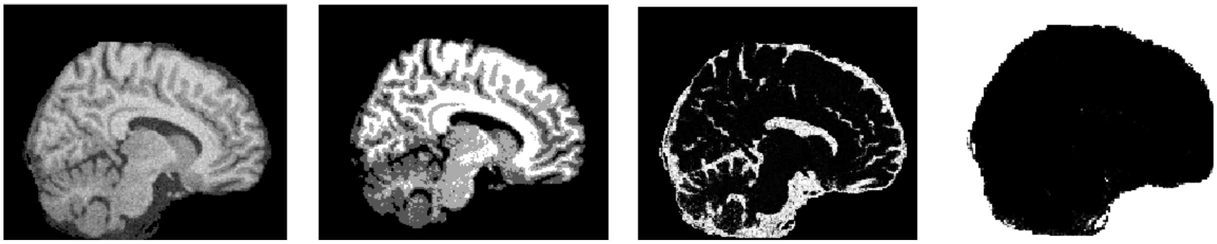

Fig. 9. Comparing of segmentation results for no720_100S image, respectively from left to right: The original image, ARKFCM segmentation result, FCM segmentation result, SFCM2D segmentation result

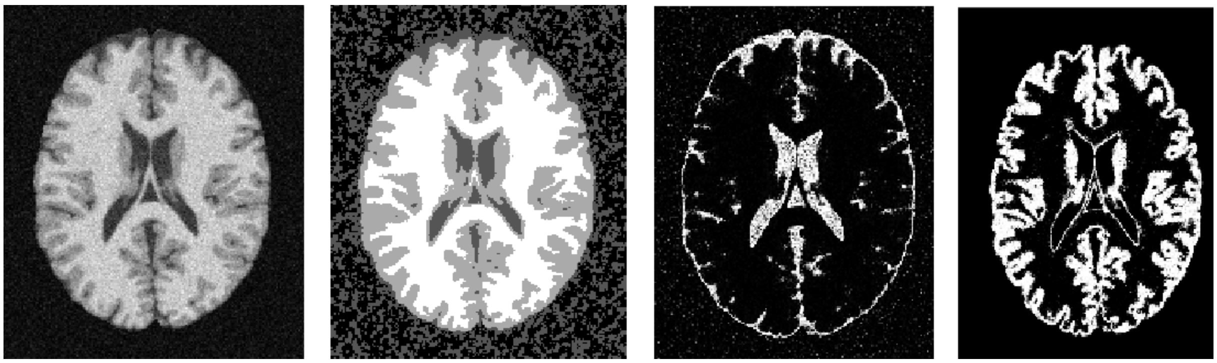

Fig. 10. Comparing of segmentation results for rice10_91A image, respectively from left to right: The original image, ARKFCM segmentation result, FCM segmentation result, SFCM2D segmentation result

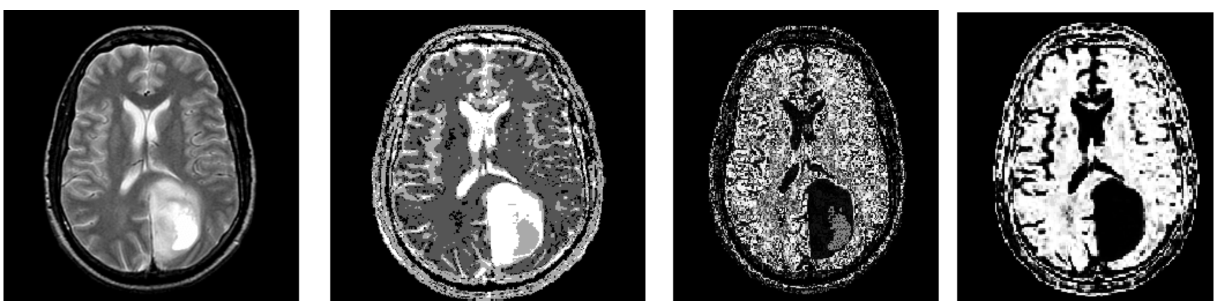

Fig. 11. Comparing of segmentation results for MRI image which is without noise and weighted operation, respectively from left to right: The original image, ARKFCM segmentation result, FCM segmentation result, SFCM2D segmentation result.

4 Future Work and Conclusion

Segmentation is a significant part of image analysis, hence the field of research is ongoing although a wide literature is available. In this study ARKFCM algorithm was implemented on data set of 5 images with different features, we used this data set and implemented ARKFCM and two other algorithms (FCM, SFCM2D) on this data set and another type of MRI image without noise and not weighted, then compared segmented results of these three algorithms and concluded the ARKFCM algorithm has better performance for any type of image, also FCM has better performance for Brats1, Brat2, no720_100A, no720_100S images, instead SFCM2D algorithm has better performance for rice10_91A image and image without noise and not weighted. The methods used in this study are practicable for the evaluation of MRI images and in the future can be implemented on other types of medical images like CT. In addition, being sensitive to severe noise might be resolved by implanting an edge detection technique within the clustering process.

5 References

[1] H. Abdellahoum, N. Mokhtari, A. Brahimi, A. Boukra Csfcm: An Improved Fuzzy C-Means Image Segmentation Algorithm Using A Cooperative Approach. 2020. doi:10.1016/J.Eswa.2020.114063

[2] Y. Yang, S. Huang, Image Segmentation By Fuzzy C-Means Clustering Algorithm With A Novel Penalty Term. Image Segmentation By Fuzzy C-Means Clustering Algorithm With A Novel Penalty Term. Request Pdf, 2007.

[3] S. Naz, H. Majeed and H. Irshad, "Image segmentation using fuzzy clustering: A survey," 2010 6th International Conference on Emerging Technologies (ICET), 2010, pp. 181-186, doi: 10.1109/ICET.2010.5638492.

[4] B. Ahmed, M. Al-Ani, "Digital Medical Image Segmentation Using Fuzzy C-Means Clustering", UHD Journal of Science and Technology,4,1, pp.51-58, 2020 . doi: 10.21928/uhdjst.V4n1y2020.Pp51-58.

[5] A. Elazab, C. Wang, F. Jia, J. Wu, G. Li, and Q. Hu, "Segmentation Of Brain Tissues From Magnetic Resonance Images Using Adaptively Regularized Kernel-Based Fuzzy C-Means Clustering", Computational and Mathematical Methods in Medicine, 2015. doi:10.1155/2015/485495

[6] J. Cai, Segmentation and Diagnosis of Liver Carcinoma Based on Adaptive Scale-Kernel Fuzzy Clustering Model for CT Images. J Med Syst 43, 322 (2019). doi:10.1007/s10916-019-1459-2

[7] Bing Nan Li, Chee Kong Chui, Stephen Chang, S.H. Ong, "Integrating spatial fuzzy clustering with level set methods for automated medical image segmentation", Computers in Biology and Medicine, 41, 1, pp. 1-10, 2011, h doi:10.1016/J.Compbiomed.2010.10.007

[8] N. Dhanachandra, Y.J. Chanu, "An image segmentation approach based on fuzzy c-means and dynamic particle swarm optimization algorithm". Multimed Tools Appl 79, 18839–18858 (2020). doi:10.1007/s11042-020-08699-8

[9] R. Kalam, C. Thomas, M. A. Rahiman, "Gaussian Kernel Based Fuzzy C-Means Clustering Algorithm For Image Segmentation", Computer Science & Information Technology. 6, pp.47-56, 2016. doi: 10.5121/csit.2016.60405.

[10] R.Suganya, R.Shanthi. "Fuzzy C- Means Algorithm- A Review", International Journal of Scientific and Research Publication, 2012. http://www.ijsrp.Org/Research-Paper-1112/ijsrp-P1168.pdf (last Access on 29.12.2021)

[11] P. Kaur, , T. Chaira, "A novel fuzzy approach for segmenting medical images", Soft Comput 25, pp. 3565–3575, 2021. doi:10.1007/s00500-020-05386-6

[12] C. Narmatha, S.M. Eljack, A.A.R.M. Tuka, "A hybrid fuzzy brain-storm optimization algorithm for the classification of brain tumor MRI images", J Ambient Intell Human Comput, 2020. doi:10.1007/s12652-020-02470-5