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Invasive weed optimization and Kernel Fuzzy *C*-Means Based MRI brain tissue segmentation

K. Venkatesh Sharma

Department of Computer Science and Engineering, CVR College of Engineering, Telangana, India

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***Abstract*—**In recent years, clustering has become well known for various researchers due to various application fields like communication, wireless networking, and biomedical domain and so on. So, much different research has already been made by the researchers to develop an improved algorithm for clustering. An optimization is one of the well-known processes that has been effectively utilized for clustering. In this paper, Invasive weed optimization (IWO) based centroid initialization for fuzzy c-means clustering (FCM) in medical image segmentation (KFCM-IWO-MIS) is proposed. For MRI brain tissue segmentation, KFCM is most preferable technique because of its performance accuracy. The major limitation of the conventional KFCM is random centroids initialization, because it leads to raising the execution time to reach the best resolution. In order to accelerate the segmentation process, IWO is used to adjust the centroids of required clusters. The quantitative measures of results were compared using the metrics are number of iterations and processing time. The number of iterations and processing of KFCM-IWO-MIS method take minimum value while compared to conventional KFCM. The KFCM-IWO-MIS method is very efficient and faster than conventional KFCM for brain tissue segmentation.

***Keywords*—** clustering, centroid initialization, Invasive weed optimization(IWO), Kernel fuzzy *C*-means (KFCM), MRI brain tissue segmentation

I. INTRODUCTION

Patients with brain cancer have limited survival time with inevitable recurrence and subsequent passing, and medical procedure is the first-line treatment. The average survival period for patients with high-grade brain cancer is roughly 14 months, however individual survival is heterogeneous [1-2]. However, surgery-inflicted neurological deficits are related with poorer survival; in this manner, it is imperative to achieve extensive resection of cancer tissue without compromising non-cancer tissue [3-4]. Different innovative advances have made significant commitments in medical procedure intra operative Magnetic Resonance Imaging (MRI) and Computed Tomography (CT), ultrasound, Raman spectroscopy, and fluorescence-guided resections; however, these advances have advantages and dis-advantages in brain cancer recognition [5-10].

Segmentation is the most difficult process because of the normal and abnormal structures in the brain Tissues [11]. In this KFCM-IWO-MIS proposed system, a clustering method for segmentation is considered. Clustering is a process of partitioning or grouping a set of unlabeled objects into a number of clusters in such a way that similar objects are allowed to one cluster. The main approaches in clustering are Crisp clustering (CC) (or Hard Clustering (HC)) [12], FCM algorithm, spectral clustering [13], hierarchical methods (e.g., tree search method) competitive learning algorithms (e.g., the self-organizing map and Iterative Self-Organizing Data Analysis (ISODA) [14]), and distribution-based methods (e.g., Expectation Maximization (EM) system [15]), and density based methods [16], [17]. In particular, Density-based spatial Clustering application with noise (DBSCRN) [18] and Ordering Points are used to recognize the clustering shape [19]. A characteristic of the CC techniques used to define the boundary among clusters. The major limitation of the CC technique is boundaries among clusters cannot be obviously defined. Some Brain structure may belong to more than one cluster. In the pattern classification FC method provides a better clustering effect [20], [22]. FCM is an iterative algorithm [23]. FCM is good at resolving the ambiguities and uncertainties in the image [24]. However, FCM can't deal with the intensity in homogeneity and more difficult to reduce the noise. The application of brain tumour recognition is introduced by using modified FCM system. In that, a comprehensive feature vector space is used for segmentation which is followed by the kernel tricks. The KFCM system is extended which incorporates the neighbourhood terms into its objective function [25]. The goal of FCM is to discover cluster centroids and that diminish the objective function.

The KFCM is derived from the original FCM based on the 'kernel method' [26]. By applying kernel tricks, the KFCM system attempts to address this problem by charting data with nonlinear feature extraction [27]. Optimization algorithms are introduced for grouping process. In optimization-based clustering most of the research is concentrated in the squared error and they have used some optimization techniques such as Genetic algorithm GA [28], PSO [29], bacterial foraging optimization [30] simulated annealing [31], artificial bee colony [32] and Firefly System (FS) [33]. In this paper, to overcome the KFCM centroid random initialization problem the KFCM-IWO-MIS technique is introduced. The KFCM-IWO-MIS technique improves the segmentation performance. The performance parameters are dice coefficient, Jaccard co-efficient and accuracy.

This paper is composed as follows. Section II surveys several recent papers on brain tumor detection related strategies. In section III, KFCM-IWO-MIS technique is defined. The section IV shows the comparative experimental result for existing and proposed strategy. The conclusion is made in Section V.

II. RELATED WORK

Several researches are suggested by researchers in brain tumour detection. In this scenario, the brief evaluation of some important contributions to the existing literature is presented.

Ronghua Shang et al. [34] has introduced a clone kernel spatial FCM (CKS-FCM) technique. An immune clone system was used to optimize the initial Cluster centres (Cc), which enables the convergence global optimum. The spatial information is added in the objective function and CKS-FCM used a non-Euclidean distance based on kernel function to replace the Euclidean distance. The main restriction of the system is Low segmentation accuracy and Low robustness.

Elazab et al. [35] presented segmentation of brain tissues from MRI using adaptive regularized kernel based FCM (ARKFCM). ARKFCM system was classified into three steps such as average filter, median filter, and devised weighted image. The systems service the heterogeneity of grayscales in the neighborhood and exploit this measure for local contextual facts and exchange the standard Euclidean distance with Gaussian radial basis kernel functions. The main benefits are adapted to local context, improved robustness that preserves image details, independence of grouping parameters, and reduced computational costs, but the major limitation of the ARKFCM system is lower entropy.

Y.T. Chen et al. [36] proposed Independent component analysis-based kernelized fuzzy by using MIS. It has discussed the segmentation performance of six methods (k-means, FCM, KFCM, ICFCM, KWFLICM, and ICKFCM) for the simulated MRI pictures in noiseless case, noise case, and real medical images. The main drawback of the system is less accurate.

Li, Haiyang et al. [38] presented a system for MIS, called Dynamic PSO & K-means clustering system (DPSOK). Dynamic PSO (DPSO) & K-means clustering method was the base of the DPSOK system. It made DPSOK a balanced optimized algorithm by enhancing the computing technique of its inertia weight and learning factors. Experimentation outcomes showed that the DPSOK algorithm can efficiently enhance the K-means system's global search ability. DPSOK algorithm delivered better results in enhancing image segmentation quality and efficiency compared to conventional PSO K-means system.

To overcome the above mentioned drawbacks, KFCM-IWO-MIS algorithm is implemented for enhancing the performance of brain tumor segmentation and detection.

III.METHODOLOGY

Relevant Image segmentation plays a major role in many real-time applications such as pattern recognition, image coding, computer vision and medical image analysis. In this paper, KFCM-IWO-MIS algorithm is introduced for brain tissue segmentation, which is shown in Fig. 1. The objective of KFCM-IWO-MISmethod is to find the Cc that minimizes a dissimilarity (objective) function of KFCM. By iteratively updating the Cc and the membership grade for each information point, KFCM iteratively moves the Cc to the "right" position within a data set. But it's not possible to discover the best solution at an optimal time. The working of the KFCM is based upon the initial centroids so finding the centroids is most important thing in the KFCM. For this purpose, the KFCM-IWO-MIS method is an automatic centroid selection the IWO based KFCM is introduced in this paper. The KFCM-IWO-MIS method includes two modules, the IWO clustering module and the KFCM clustering module. In the initial stage, the IWO clustering module is executed for a short period for automatic clustering, forming spherical or close to spherical shape data clusters. The result from the IWO clustering module is used as the initial seed of the KFCM module. The optimized segments are Contour by Geometric active contour framework (GACF). Here, the fitness value calculated and the best fitness value is fixed as a centroid value. By using the fitness value, the IWO segmentation is processed and finally, the performance is calculated.

3.1. Fuzzy C Means Algorithm

FCM system is partitioning the dataset $\{x_k\}_{k=1}^{N}$ into c number of clusters based on the following objective function Eq. (1).

$$J_m = \sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{p} \left\| x_k - v_i \right\|^2 \tag{1}$$

Where p indicates the real number, which denotes the quantity controlling of the fuzziness of the resultant group, u_{ik}^{p} is the membership of the data point x_k belongs to the cluster i and the x_k is pixel of the image which satisfying $\sum_{i=1}^{c} u_{ik} = 1$ and v_i is the centroid of the cluster

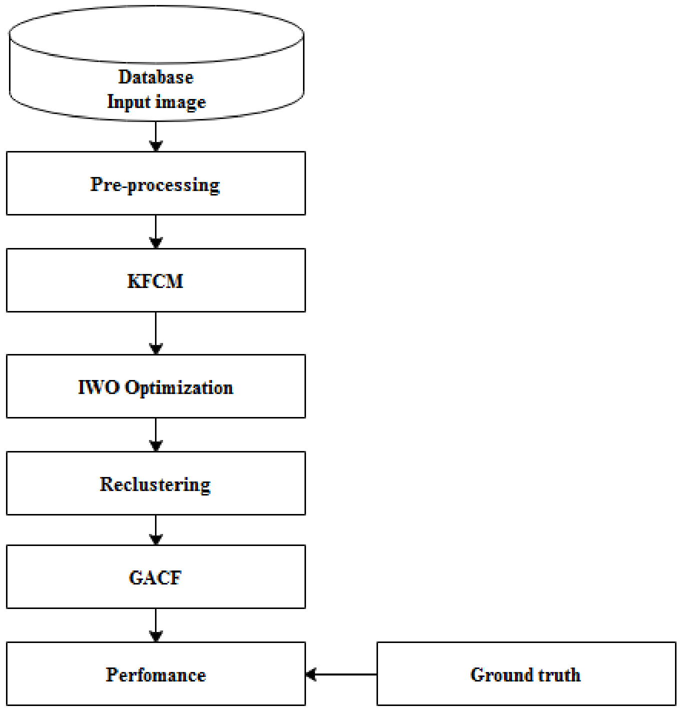


Fig. 1. KFCM-IWO-MISblock diagram

. From the above equation 1, where c is the total number of clusters and N denotes the number of data points. The FCM makes the partitioning by iteratively updating the membership values and the cluster centroids. The membership value of each data point to the every centroid value derived after updating time of each centroids that can be done by the Eq. (2).

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{\|x_k - v_i\|^2}{\|x_k - v_j\|^2} \right)^{\frac{1}{p-1}}} \quad (2)$$

The cluster centroids are updated based on the distance between the data point to the cluster centroid which is done by the following Eq. (3).

$$v_k = \frac{\sum_{k=1}^{N} x_k U_{ik}^p}{\sum_{k=1}^{N} u_{ik}^p} \quad v_i = \frac{\sum_{j=1}^{N} u_{ij}^m x_j}{\sum_{j=1}^{N} u_{ij}^m} \quad (3)$$

The objective function performs the calculation to measure the weighted sum of results between the cluster centre and data presents in the fuzzy clusters. FCM provides better segmentation results for the images, which does not have any noise. However, the FCM fails to classify the noisy data because of the irregularities of the feature data, which leads to assigning the membership values to become erroneous. This is the main reason for improper segmentation occurs during the processing of a noisy image by the FCM.

3.2. Kernelized Fuzzy C Means (KFCM)

To overcome the regular FCM difficulties, the KFCM algorithm is introduced. With the help of a nonlinear mapping function (MF), the KFCM converts the input data in the image plane into advanced dimensional feature space. The complex and nonlinear separable problem in the input plane can be converted with the guidance of the mapping function into linearly separable in the future space. Then, the FCM can perform its operation with the derived feature space. The objective function of the KFCM is defined in Eq (4).

$$\begin{aligned} J_m &= \sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^p \left\| \varphi(x_k) - \varphi(v_i) \right\|^2 \\ &= 2\sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^p \left(1 - k\left(x_k - v_i\right)\right) \end{aligned} \quad (4)$$

Here φ is the MF. Here the Gaussian Kernel Function (GKF) for non-linear mapping of the image plane into the linear high dimensional feature space. The GKF is presented in the following below equation (5).

$$K(x,y) = \exp\left(-d(x,y)^2 / \sigma^2\right) \quad (5)$$

The Gaussian kernel neutral function is presented in the following below equation (6)

$$\begin{aligned} J_m &= \sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^p \left\| \varphi(x_k) - \varphi(v_i) \right\|^2 \\ &= 2\sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^p \left(1 - K\left(x_k, v_i\right)\right) \end{aligned} \quad (6)$$

Where the membership function (MF) and the updating the centroid is calculated by the following Eq 5 and 6 respectively.

$$u_{ik} = \frac{\left(1 - K\left(x_k, v_i\right)\right)^{-1/(p-1)}}{\sum_{i=1}^{c}\left(1 - K\left(x_j, c_i\right)\right)^{-1/(p-1)}} \quad (7)$$

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^p K\left(x_k - v_i\right) x_k}{\sum_{k=1}^{n} u_{ik}^p K\left(x_k, v_i\right)} \quad (8)$$

3.3. Extreme Learning (EL) Machine

The charting function of KFCM method makes the input data into a high dimensional feature vector, which helps the FCM to handle the noisy image. However, high speed processing of dimensional feature vectors demands a number of iterations, which takes more execution time to make the MF suitable for image segmentation. Due to the standard MF, the similar objects in an image is not grouped in a single partition. To solve this limitation, we utilize the EL algorithm, which supports to make the MF based on patterns in the image by learning methodology.

The EL machines are used in the ANN for training the network. In this paper, the adaptive learning techniques used to predict the future value of the fuzzy membership function (FM), which leads to reduced running time of the clustering process. The following Eq. (6) is used to predict the future value of the FM values.

$$u_{ik}^{\wedge} = \eta\left(\frac{1}{(u_{ik}X)}\right)Y \quad (6)$$

Where $u_{ik}^{\wedge}$ represents the future membership matrix and u_{ik} represents the existence membership matrix. The learning rate is represented by η and the X indicates the input matrix and Y specifies current partitioned matrix. The future centroid can be calculated using the following Eq (7).

$$v_i^{\wedge} = \frac{\sum_{k=1}^{n} u_{ik}^{\wedge} K\left(x_k - v_i\right) x_k}{\sum_{k=1}^{n} u_{ik}^{\wedge} K\left(x_k, v_i\right)} \quad (7)$$

3.4. Invasive weed optimization

The IWO algorithm is a numerical stochastic and derivative free optimization and it was developed by Mehrabian and Lucas for continuous optimization. Inspired by the colonizing behavior of weed plants, and the IWO algorithm iterates with three consecutive processes: reproduction, spatial dispersal, and competitive exclusion. All of the weeds in the IWO algorithm take part in the reproduction process, but the fertilities of different weeds are not equivalent. The number of seeds produced by a weed depends on its fitness. Fitter weeds produce more seeds than less fit weeds. The seeds of weeds are randomly scattered in the search area with a regular distribution with mean equal to zero and an adaptive standard deviation. After reproduction, the seeds and weeds enter a competition and the winners are considered as the weeds for the next generation. The sketch procedure of the basic IWO algorithm can be summarized as follows

Initialization: The IWO algorithm is formed with a population of initial weeds, $A = a_1, a_2, ...a_{ps}$

Where a_{ps} is the size of the initial population, and each of the weeds $ai = a_{i1}, a_{i2}, ...a_{in}$ is an n-dimensional real-valued vector. For each dimension a_{ik} of a_i it can be generated as follows Eq. (8).

$$a_{ik} = lb_k + r(up_k - lb_k), \quad i = 1,2,...ps, \quad k = 1,2,...n$$
(8)

Where r is a uniform random number in the range of $[0,1]$, lb_k and ub_k represent the lesser and higher bounds for the dimension k respectively. The bounds are problem dependent.

Reproduction: Each of the weeds generates seeds in the reproduction process. The higher the weed's fitness, the more seeds it produces. Denote s_i the amount of seeds produced by weed a_i. Wedecide a_i as follows Eq.9.

$$s_i = floor(s_{\min} + \frac{s_{\max} - s_{\min}}{f_{\max} - f_{\min}})X(f(a_i) - f_{f\min}) \quad (9)$$

Where, $f(a_i)$ is the fitness of a_i, $floor()$ is a function which rounds the elements to the nearest integers towards minus infinity. $s_{\max}$ and $s_{\min}$ are two algorithmic parameters, which define the amount of seeds produced by the worst and best weeds in the population, separately.The seeds of a weed a_i spread closely to the weed. The IWO algorithm generates a seed for a_i according to a normal distribution. Denote $a_i' = \{a_{i1}', a_{i2}', ..a_{in}'\}$ a seed produced by a_i.it is shown in Eq. 10.

$$a_{ik} = a_{1k} + N(0, \sigma^2), k = 1,2,..n \quad (10)$$

Where $N(0, \sigma^2)$ is a function returns a normally distributed random number with mean equal to zero and the standard deviation σ. σ is a parameter determined in the Spatial Dispersal Step.

Spatial Dispersal: The seeds spread around their parent weeds in a normal distribution. To ensure that the probability of dropping a seed in a distant area reductions non-linearly at each iteration which results in clustering fitter plants and elimination of inappropriate plants. The standard deviation σ of the normal distribution is adaptively reduced from a specified initial value σ_0 to a final value, σf as follows Eq.(11).

$$\sigma_{iter} = \frac{(iter_{\max} - iter)^x}{(iter_{\max})^x} X(\sigma_0 - \sigma_f) + \sigma_f \quad (11)$$

Competitive Exclusion: All of the weeds and their seeds are combined together to form a populace for the next group. If the size of the population is larger than a given maximum value, namely $ps_{\max}$, the weeds with lower fitness are eliminated. The reproduction and competitive mechanism give a chance for less fit weeds to reproduce. If the reproduction generate fitter offspring, that generated offspring can survive in the competition.

Termination Condition: Repeat Reproduction through Competitive Exclusion until a given termination condition, such as the concentrated amount of iterations or the maximum elapsed CPU time, is met.

IV. RESULTS AND DISCUSSION

It The KFCM-IWO-MIS system was performed with the help of T1-WCEMRI database. The KFCM-IWO-MIS system was analyzed with the help of MATLAB stimulator software version 2018b. The entire work is done by using I3 system with 2 GB RAM. The maximum amount of iterations 2 is used in IWO clustering. This iteration is sufficient to yield the optimal centroids for this KFCM-IWO-MIS method. Both quantitative and qualitative validations were used for the performance evaluation. The performance of the KFCM-IWO-MIS methodology was compared in terms of dice coefficient, Jaccard co-efficient and accuracy.

4.1. Performance measure

In segmentation validation, the dice coefficient is expressed in terms of TP, TN, FP and FN counts, which is obtained by matching the segmented result to the ground truth image. The general formula utilized to calculate the dice coefficient is represented in the Eq. (25).

$$Dicecoefficient = \frac{2TP}{(2TP+FP+FN)} \qquad (25)$$

Where, the dice coefficient value "0" shows no similarity between the results and the value "1" demonstrates the similarity between the output and ground truth image.

In Jaccard coefficient, the TP values are detected by the overlaps among the manually segmented ground truth tumor labels and the machine generated tumor labels. The general formula used to calculate Jaccard co-efficient is denoted in the Eq. (26).

$$Jaccardcoefficient = \frac{TP}{FP+FN+TP} \qquad (26)$$

Accuracy:

The degree of conformance among a measurement of an observable quantity and a recognized standard or specification that indicates the true value of the quantity presented in equation (27).

$$\text{Accuracy} = \frac{tp+tn}{tp+fp+tn+fn} (27)$$

Where, TP is represented as true positive, FP is denoted as false positive, TN is stated as true negative and FN is specified as false negative.

4.2. Experimental result on T1-WCEMRI dataset

In this experimental analysis, T1-WCEMRI dataset is assessed for comparing the dice, Jaccard coefficient and accuracy performance of FCM and GA-KFCM and the KFCM-IWO-MIS which is shown in the table 1. The T1-WCEMRI dataset contains 3064 images with three classes of brain images: meningioma, glioma and pituitary tumour. The performance evaluated example images are shown in the table.1.

Table.2. shows the result comparison for different image. In that, 5 different data set are taken and which are analyzed by KFCM, IWO optimization and SM-GFCA contour are presented. From the KFCM the input images is segmented, the KFCM segmented outputs are given to the IWO optimization. In that, fitness value is calculated and the best fitness is fixed as a centroid value. By using the centroid values GACF contours are framed

From table 1. Analysis shows that the KFCM-IWO-MIS technique provides much better results. The average of the KFCM-IWO-MIS technique's Dice coefficient is 0.6857 and average of Jaccard coefficient is 0.5962 and the PSO-KFCM delivers 0. 0.5658 of dice coefficient. Similarly, average Jaccard coefficient of the PSO-KFCM techniques is 0.3444. The average accuracy of the PSO-KFCM is 96.1383, and the KFCM-IWO-MIS technique provides 97.4577 accuracy which is much better compared to other existing systems.

Comparative analysis

Table.3 and Fig.2. Presents the comparative study of existing work and the proposed work performance. H. Ali, M. Elmogy, *et al.* [38] proposed a new brain image segmentation system, which was based on morphological pyramid with FCM clustering. Initially, a wavelet multi-resolution was developed in order to maintain spatial context among the pixels. Then, morphological pyramid was utilized to increase the sharpness of brain images. Finally, segmentation was carried-out using FCM clustering. The experimental outcome shows that the developed methodology achieved 96% of classification accuracy. In order to validate the KFCM-IWO-MIS method accuracy. Whereas, the KFCM-IWO-MIS work achieves 97.4577% of accuracy that was higher than the existing works.

V. CONCLUSION AND FUTURE SCOPE

Table.2 and Fig.2. Presents the comparative study of existing work and the proposed work performances. Ali, M. Elmogy, *et al.* [38] proposed a new brain image segmentation system, which was based on morphological pyramid with FCM clustering. Initially, a wavelet multi-resolution was developed in order to maintain spatial context among the pixels. Then, morphological pyramid was utilized to increase the sharpness of brain images. Finally, segmentation was carried-out using FCM clustering. The experimental outcome shows that the developed methodology achieved 96% of classification accuracy. In order to validate the KFCM-IWO-MIS method accuracy. Whereas, the KFCM-IWO-MIS work achieves 97.4577% of accuracy that was higher than the existing works.

REFERENCES

[1] Pilleron, S., Sarfati, D., Janssen-Heijnen, M., Vignat, J., Ferlay, J., Bray, F. and Soerjomataram, I., 2018. Global cancer incidence in older adults, 2012 and 2035: A population-based study. International journal of cancer.

[2] Ferlay, J., Soerjomataram, I., Dikshit, R., Eser, S., Mathers, C., Rebelo, M., Parkin, D.M., Forman, D. and Bray, F., 2015. Cancer incidence and mortality worldwide: sources, methods and major patterns in GLOBOCAN 2012. International journal of cancer, 136(5), pp.E359-E386.

[3] Thambi, R. and Kandamuthan, S., 2017. Histopathological Analysis of Brain Tumors-A Seven Year Study from a Tertiary Care Centre in South India. Journal of clinical and diagnostic research: JCDR, 11(6), p.EC05.

[4] Lacroix, M., Abi-Said, D., Fourney, D.R., Gokaslan, Z.L., Shi, W., DeMonte, F., Lang, F.F., McCutcheon, I.E., Hassenbusch, S.J., Holland, E. and Hess, K., 2001. A multivariate analysis of 416 patients with glioblastoma multiforme: prognosis, extent of resection, and survival. Journal of neurosurgery, 95(2), pp.190-198.

[5] Sanai, N., Polley, M.Y., McDermott, M.W., Parsa, A.T. and Berger, M.S., 2011. An extent of resection threshold for newly diagnosed glioblastomas. Journal of neurosurgery, 115(1), pp.3-8.

[6] McGirt, M.J., Mukherjee, D., Chaichana, K.L., Than, K.D., Weingart, J.D. and Quinones-Hinojosa, A., 2009. Association of surgically acquired motor and language deficits on overall survival after resection of glioblastoma multiforme. Neurosurgery, 65(3), pp.463-470.

[7] Kut, C., Chaichana, K.L., Xi, J., Raza, S.M., Ye, X., McVeigh, E.R., Rodriguez, F.J., Quiñones-Hinojosa, A. and Li, X., 2015. Detection of human brain cancer infiltration ex vivo and in vivo using quantitative optical coherence tomography. Science translational medicine, 7(292), pp.292ra100-292ra100.

[8] Rygh, O.M., Selbekk, T., Torp, S.H., Lydersen, S., Hernes, T.A.N. and Unsgaard, G., 2008. Comparison of navigated 3D ultrasound findings with histopathology in subsequent phases of glioblastoma resection. Acta neurochirurgica, 150(10), p.1033.

[9] Ji, M., Orringer, D.A., Freudiger, C.W., Ramkissoon, S., Liu, X., Lau, D., Golby, A.J., Norton, I., Hayashi, M., Agar, N.Y. and Young, G.S., 2013. Rapid, label-free detection of brain tumors with stimulated Raman scattering microscopy. Science translational medicine, 5(201), pp.201ra119-201ra119.

[10] Özduman, K., Yıldız, E., Dinçer, A., Sav, A. and Pamir, M.N., 2014. Using intraoperative dynamic contrast-enhanced T1-weighted MRI to identify residual tumor in glioblastoma surgery. Journal of neurosurgery, 120(1), pp.60-66.

[11] Zausinger, S., Scheder, B., Uhl, E., Heigl, T., Morhard, D. and Tonn, J.C., 2009. Intraoperative computed tomography with integrated navigation system in spinal stabilizations. Spine, 34(26), pp.2919-2926.

[12] Muñoz, X., Freixenet, J., Cufı, X. and Martı, J., 2003. Strategies for image segmentation combining region and boundary information. Pattern recognition letters, 24(1), pp.375-392.

[13] Krinidis, S. and Chatzis, V., 2010. A robust fuzzy local information C-means clustering algorithm. IEEE Transactions on Image Processing, 19(5), pp.1328-1337.

[14] Shi, J. and Malik, J., 2000. Normalized cuts and image segmentation. IEEE Transactions on pattern analysis and machine intelligence, 22(8), pp.888-905.

[15] [15]. Andersson, M., Gudmundsson, J. and Levcopoulos, C., 2004. Approximate distance oracles for graphs with dense clusters. Lecture notes in computer science, 3341, pp.53-64.

[16] Govaert, G. and Nadif, M., 2005. An EM algorithm for the block mixture model. IEEE Transactions on Pattern Analysis and machine intelligence, 27(4), pp.643-647.

[17] Wang, X.F. and Huang, D.S., 2009. A novel density-based clustering framework by using level set method. IEEE Transactions on knowledge and data engineering, 21(11), pp.1515-1531.

[18] Zhang, J. and Kerekes, J., 2015. An adaptive density-based model for extracting surface returns from photon-counting laser altimeter data. IEEE Geoscience and Remote Sensing Letters, 12(4), pp.726-730.

[19] Ester, M., Kriegel, H.P., Sander, J. and Xu, X., 1996, August. A density-based algorithm for discovering clusters in large spatial databases with noise. In Kdd (Vol. 96, No. 34, pp. 226-231).

[20] Omrani, A. and Santhisree, K., 2011, May. Clustering sequential data with OPTICS. In Communication Software and Networks (ICCSN), 2011 IEEE 3rd International Conference on (pp. 591-594). IEEE.

[21] De Marsico, M., Nappi, M., Riccio, D. and Wechsler, H., 2013. Robust face recognition for uncontrolled pose and illumination changes. ieee transactions on systems, man, and cybernetics: systems, 43(1), pp.149-163.

[22] Sheng, W., Chen, S., Xiao, G., Mao, J. and Zheng, Y., 2015. A biometric key generation method based on semisupervised data clustering. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 45(9), pp.1205-1217.

[23] Zhu, L., Chung, F.L. and Wang, S., 2009. Generalized fuzzy c-means clustering algorithm with improved fuzzy partitions. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 39(3), pp.578-591.

[24] J.C.Bezdek, Pattern Recognition with Fuzzy Objective Function Algorithms, Kluwer Academic Publishers, Norwell, MA, USA, 1981.

[25] Yang, Y., Zheng, C. and Lin, P., 2005. Fuzzy C-means clustering algorithm with a novel penalty term for image segmentation. Optoelectronics Review, 13(4), p.309.

[26] Girolami, M., 2002. Mercer kernel-based clustering in feature space. IEEE Transactions on Neural Networks, 13(3), pp.780-784.

[27] Chen, S. and Zhang, D., 2004. 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), 34(4), pp.1907-1916.

[28] Maulik, U. and Bandyopadhyay, S., 2000. Genetic algorithm-based clustering technique. Pattern recognition, 33(9), pp.1455-1465.

[29] Premalatha, K. and Natarajan, A.M., 2008. A new approach for data clustering based on PSO with local search. Computer and Information Science, 1(4), p.139.

[30] Wan, M., Li, L., Xiao, J., Wang, C. and Yang, Y., 2012. Data clustering using bacterial foraging optimization. Journal of Intelligent Information Systems, 38(2), pp.321-341.

[31] Selim, S.Z. and Alsultan, K., 1991. A simulated annealing algorithm for the clustering problem. Pattern recognition, 24(10), pp.1003-1008.

[32] Zhang, C., Ouyang, D. and Ning, J., 2010. An artificial bee colony approach for clustering. Expert Systems with Applications, 37(7), pp.4761-4767.

[33] Senthilnath, J., Omkar, S.N. and Mani, V., 2011. Clustering using firefly algorithm: performance study. Swarm and Evolutionary Computation, 1(3), pp.164-171.

[34] Shang, R., Tian, P., Jiao, L., Stolkin, R., Feng, J., Hou, B. and Zhang, X., 2016. A spatial fuzzy clustering algorithm with kernel metric based on immune clone for SAR image segmentation. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 9(4), pp.1640-1652.

[35] Elazab, A., Wang, C., Jia, F., Wu, J., Li, G. and Hu, Q., 2015. Segmentation of brain tissues from magnetic resonance images using adaptively regularized kernel-based fuzzy-means clustering. Computational and mathematical methods in medicine, 2015.

[36] Chen, Y.T., 2017. Medical Image Segmentation Using Independent Component Analysis-Based Kernelized Fuzzy-Means Clustering. Mathematical Problems in Engineering, 2017.

[37] Li, H. He, and Y. Wen, “Dynamic particle swarm optimization and K-means clustering algorithm for image segmentation”, Optik - International Journal for Light and Electron Optics, Vol.126, No.24, pp.4817-4822, 2015.

[38] H. Ali, M. Elmogy, E. El-Daydamony and A. Atwan, “Multi-resolution MRI brain image segmentation based on morphological pyramid and fuzzy c-mean clustering”, Arabian Journal for Science and Engineering, Vol.40, No.11, pp.3173-3185, 2015.

Table 1. Dice and Jaccard coefficient comparison of PSO-KFCM and the KFCM-IWO-MIS

Class	**Clustering technique**	**Dice coefficient**	**Jaccard coefficient**	**Accuracy**
Meningioma	PSO-KFCM	0.26158	0.1625	94.1253
	KFCM-IWO-MIS	**0.4075**	**0.3041**	**96.4890**
Glioma	PSO-KFCM	0.4765	0.2511	93.7741
	KFCM-IWO-MIS	**0.92380**	**0.88347**	**96.9931**
Pituitary	PSO-KFCM	0.5847	0.3570	97.0235
	KFCM-IWO-MIS	**0.7258**	**0.6010**	**98.8912**

Table 2. Comparative analysis of proposed and existing methodologies

References	**Database**	**Segmentation methodology**	**Accuracy**
H. Ali, M. Elmogy, *et al.* [38]	Brain Web (DS1), BRATS (DS2)	Morphological pyramid with FCM clustering technique	96%
Proposed	**T1-WCEMRI**	KFCM-IWO-MIS	**97.4577%**

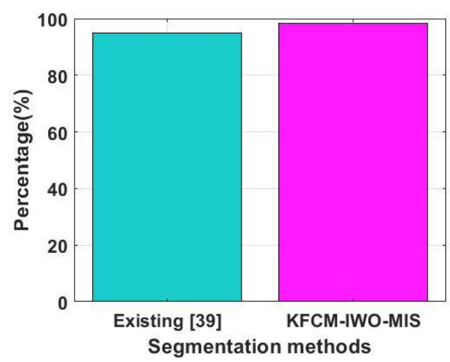
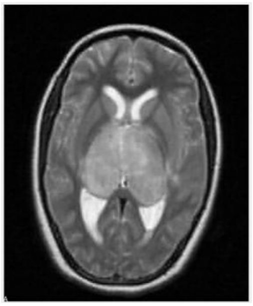
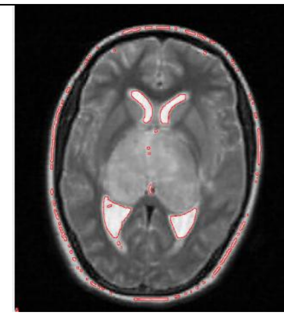
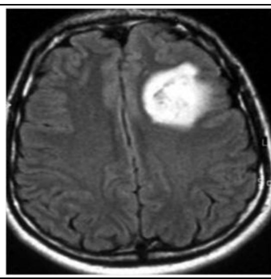
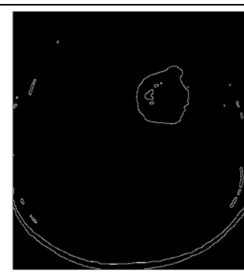
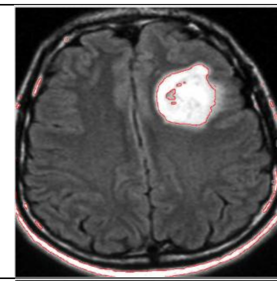
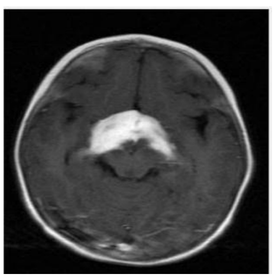
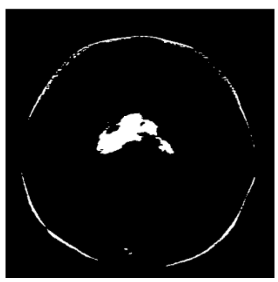
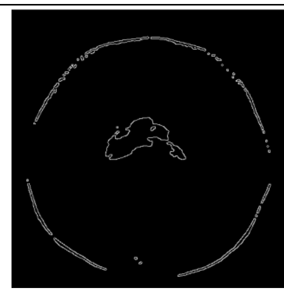
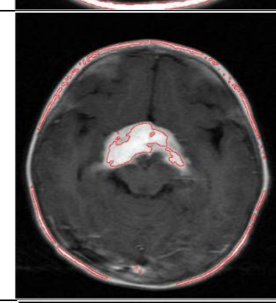
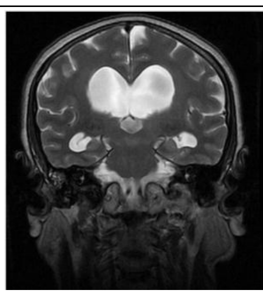
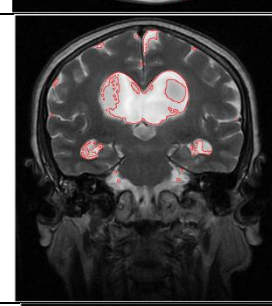


Fig.2. Average accuracy comparison of KFCM-IWO-MIS and existing methodologies

Table.3. shows the result comparison for different image

Sl.No	Input image	KFCM segmented image	IWO optimized image	GACF image
1				
2				
3				
4				
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