EAI Endorsed Transactions
on Pervasive Health and Technology Research Article EAI.EU

Enhanced Brain Tumour MRI Segmentation using K-means with machine learning based PSO and Firefly Algorithm

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Abstract

INTRODUCTION: Medical image segmentation is usually integrated as a critical step in medical image analysis, often associated with numerous clinical applications. Magnetic Resonance Imaging (MRI) provides detailed visualization of the various anatomical structures decisive for interventions and surgical plans.
OBJECTIVES: The objective of this paper is to design and apply an enhanced brain tumor MRI segmentation using K-mean with K-means as machine learning based Particle Swarm Optimization (PSO) and Firefly Algorithm (FA).
METHODS: A novel fitness function of Swarm Based PSO works on velocity variation is introduced, which enhances the segmented regions. The traditional k-means algorithm is enhanced by applying PSO to the segmented part. Another extension of Swarm Intelligence named Firefly is applied to compare the results of the PSO based segmentation, and Firefly based segmentation is used.
RESULTS: The simulation results are evaluated in terms of precision (98%), recall (0.95), f-measure (0.96), accuracy (97%), and segmentation time (2.63s) to measure the image segmentation the quality of main results obtained.
CONCLUSION: Comparative studies have shown that the proposed design using k-means combined with FA exhibited high accuracy and precision in detecting brain tumor RoI.

Keywords: Magnetic Resonance Imaging (MRI), K-means, Machine Learning, Particle Swarm Optimization (PSO), Firefly Algorithm (FA).

Received on 08 April 2020, accepted on 19 January 2021, published on 03 February 2021

doi: 10.4108/eai.3-2-2021.168600

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1. Introduction

Image segmentation is a technique of transforming a digital image into image objects to make it more understandable. The segmentation simply modifies the image representation by labeling each and every pixel so as to ease the analysis while converting it into something that is more meaningful. Magnetic Resonance Imaging (MRI) unveils high spatial resolution anatomical details involving tissue abnormalities [1]. Brain MRI is specifically employed to unfold the sensitive information related to muscles, ligaments, tendons, nerve damage, bleeding, blood clot, etc., with inbuilt power of distinguishing soft tissues [2]. MRI segmentation approaches play a vital role in numerous applications in neurology that involve precise estimation of tumor size, tumor location, tumor volume, lesions, blood cells demarcation, therapy, and surgical planning [1,3].

Typically, the brain consists of White matter (WM), which is the main element of the nervous system that includes neuropil, glial cells, synapses, and capillaries. Gray Matter (GM) is different from WMs as it consists of a number of cell bodies with a small number of myelinated axons. In healthy tissues, the grey color is of high brightness. The function of gray matter in the brain is to see, hear, memorize, speech, take a decision, and to control yourself.

There is one more element that is present in the brain is Cerebrospinal Fluid (CSF) filled cavity. This fluid is used to fill the brain ventricles and the surrounding area of the brain covered by the subarachnoid and spinal cord. The pictorial view is, as shown in Figure 1 [4]. Precise quantitative measurement of these regions is a critical step for accurate pathological planning in brain tumor patients [5].

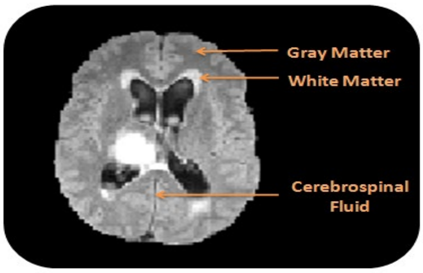


Figure 1. Brain MRI Scan

In this research, we focus on the improvement of brain tumor segmentation accuracy by utilizing the concept of the Firefly Optimization Algorithm along with the K-means technique. When the brain tumor is segmented using the k-means, the background (grey matter) and foreground (white matter) pixels of images are mixed and reduce the segmentation accuracy. So, we used the swarm-based optimization approach to solve this problem by the selection of a threshold level of pixels for separation of background and foreground data. We present a comparative analysis of two different swarm-based optimization algorithms, such as PSO and Firefly Optimization Algorithm.

Further, the organization of the paper is as follows. The paper has been divided into 5 sections: Section 2 describes the state-of-art. Section 3 covers the proposed methodology as materials and methods. The results are summarized in Section 4. The paper is finally concluded in Section 5.

2. Related Work

The present section discusses the existing MRI segmentation techniques put forward by various researchers. Derraz et al. in 2004, aimed their study for the improvement of medical diagnosis aided with improved image segmentation of MRI scans. To achieve desired results, mathematical algorithms for modeling, feature extraction, and measurement were employed to identify the diseased or abnormal regions as compared to the normal ones [6]. The improvements in the segmentation process are also observed in previous studies. Chander et al. 2011, proposed image segmentation by modifying it through the conventional Particle Swarm Optimization (PSO) approach. The experimental evaluation stated that the proposed modified PSO outperformed the existing PSO variants and could successfully deal with image segmentation issues. It was also observed that the proposed modified PSO was better than the Gaussian smoothing algorithm [7]. K-means are observed to be applied in most of the research articles when it comes to the initial segmentation procedure. Bandyopadhyay and Paul in 2013 offered a diagnostic system for the identification of brain tumors. In the proposed design, the authors divided the system into two stages to enhance the quality of image segmentation. The first one dealt with the registration process, which was then applied to adjoining layers of the brain, and the second one dealt with the fusion process between the registered images. In the later stages, improved k-means along with dual localization methodology was used to complete image segmentation. The authors have mentioned that they would consider 3D modeling for image segmentation and tumor detection as future work [8].

Zhao et al. in 2014, proposed an improved k-means approach with the utilization of PSO. In this proposed design, the PSO is employed for the generation of initial clusters. The experimental evaluation demonstrated that the modified k-means outperformed in terms of execution time as compared to k-means [9]. Jose et al. in 2014 used noise free 40 MRI scan, among which 20 scans corresponding to a brain tumor that was further divided into training and testing sets. These were fed as an input to advanced k-means, and fuzzy c means to identify tumor regions from the brain cancer image. The method involved the conversion of the grayscale and Red Green Blue (RGB) images to binary images and predicted the tumor size by calculating the while pixels of the binary image. They further predicted the tumor stage on the basis of the size and area of the tumor [10].

Saini and Verma in 2015 utilized the merits of PSO and biogeography-based optimization (BBO) algorithm for image segmentation of 3D brain scans. The proposed hybrid algorithm was found to be more consistent and flexible with a scope where multiple objectives to be utilized as functions. This functionality added to the additional reason for less execution time for hybrid as compared to individual PSO and BBO along with better results for 3D image segmentation as compared to 2D image segmentation [11]. Das and Jain in 2015 revolved their research around the optimum method for identifying the tumor regions or the abnormal regions in the brain MRI scans with the help of texture feature analysis. The study was divided into image enhancement, image segmentation, and feature extraction stage to enhance the accuracy of the results [12].

PSO combined with k-means was by Parasar and Rathod in 2017 for the segmentation of fetus ultrasound images. The evaluation of the results was done both in the presence and absence of noise. The instrumental results were obtained when compared against the seeded region growing method combined with PSO, watershed, and fuzzy c-means [13]. Ventateshan and Parthiban in 2017 proposed an image segmentation approach using the combination of PSO with fuzzy k-means and kernel fuzzy k-means. The authors have used brain MRI scans for testing the proposed architecture. Evaluation of the method is done on the bases of computation time, average intra-cluster distance, and Davies-Bouldin Index. The results showed that their hybrid is less sensitive to noise with faster convergence [14].

Hasan, in 2018, conducted a research study in which he designed a technique for automatic identification and image segmentation of MRI scans specifically for pathological regions. Initially, pre-processing of the datasets is done so as to normalize image samples. Then PSO is performed to identify the pathological regions followed by contour without edge method. The method showed an accuracy of 92% in comparison to the manual description [15]. Karegowda et al. in 2018 evaluated various image segmentation approaches for precise identification of tumor region in MRI scans. In the study performance of k-means, fuzzy c-means, PSO, and Adaptive Regularised Kernel Fuzzy c-means were evaluated in terms of segmentation accuracy, structural similarity index, normalized cross-correlation, Mean square error and signal-to-noise ratio. The experimental results had demonstrated that the segmentation based on k-means and fuzzy c-means outperformed as compared to PSO and Adaptive Regularised Kernel Fuzzy c-means [16].

Arun Kumar et al. 2019 proposed an enhanced automated technique for brain tumor identification and segmentation. In the architecture, k-means held the major position and was employed in the initial stages to improve the quality of MRI scans and transformed them into grayscale images. The authors aimed at image enhanced coupled with image identification and classification for a computerized, accurate prediction of a brain tumor [17]. Recently, Hrosik et al. in 2019 proposed a combination of k-means and firefly algorithms for improvement of image segmentation for brain MRI scans obtained from Harvard Whole Brain Atlas datasets. The literature evaluation of the results has shown that the proposed combination outperformed for the image segmentation quality in terms of a peak to noise, root square mean error, and similarity index [18]. Nanda et al. (2019) have worked on to improve image segmentation of MRI images of brain using K-means with GAO (Galatic Swarm Optimization) algorithm. The researchers have used Otsus entropy technique to resolve the segmentation problem. This approach is used to minimize the inter-cluster distance [19].

Dobe et al. (2019) have presented a rough set-based K-means algorithm for the detection of tumor from the MRI image. The segmentation through k-means is followed by the global thresholding and morphological operation. The designed algorithm performs better in contrast to the past techniques [20].

Alam et al. (2019) have used template-based K-means approach in combination to fuzzy c means for the tumor detection from the MRI image. An appropriate selection of templates has been performed using K-means. Whereas, modified membership has been evaluated by determining distance between the centroids. As only intensity point is taken into consideration therefore, the obtained image is highly immune to noise [21].

Chander et al. (2020) have used K-means to segment MRI image so that accurate part of the image can be extracted. To enhance the detection accuracy of the designed system Support Vector Machine (SVM) is used in combination to K-means algorithm. The results show that higher accuracy has been obtained using linear kernel [22]. Though the usage of Swarm Intelligence is not new in the contrast of image segmentation and its optimization, this paper adds up a novel fitness function and updates the behavior of both the algorithms PSO and Firefly for the segmentation optimization.

In the existing work, segmentation of white matter (foreground) and grey matter (background) was done on the basis of traditional segmentation techniques but they do not cover the error minimization during the segmentation of MRI image foreground and background. The classification accuracy of a brain tumour depends on the segmentation accuracy, if segmentation is proposer, then the classification becomes more accurate. So, this article introduces the concept of improvisation of segmentation techniques using the swarm-based meta-heuristic algorithms like PSO and FFA. To evaluate the impact of meta-heuristic algorithms, we presented a comparative model for MRI brain tumour segmentation using traditional as well as improved approaches.

3. Materials and Method

The proposed methodology takes the raw data as input and applies k-means for the segmentation of the image. The segmentation process is common in all the proposed methods. The difference is noticed when it comes to optimization.

It is observed that the original uploaded image requires a little filter to be applied in order to be processed further. As shown in Figure 2, the original image is enhanced first to label it further. Greyscale labeling is difficult, and hence it is converted to color scale for further labeling. Color labeling results in a better marking of the tumor region, as shown in Figure 2.

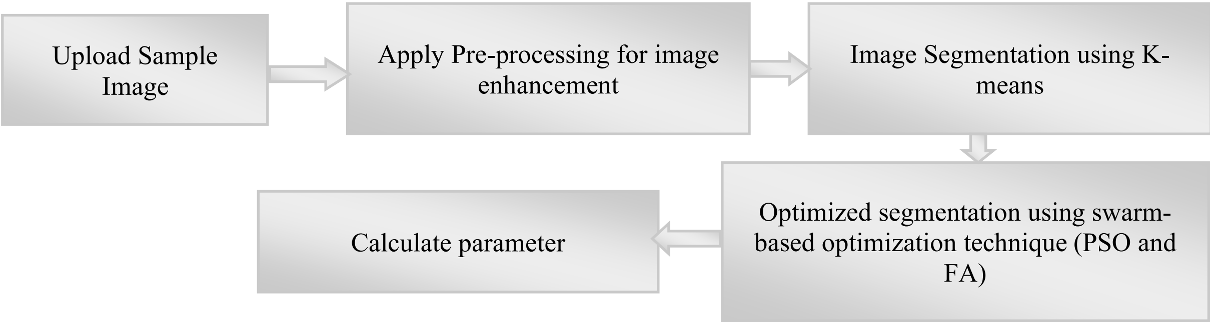


Figure 2. Workflow Diagram

3.1 Dataset

Experimental analysis is done on the Brain Tumor Segmentation (BraTS) standard dataset and it contains multimodal Magnetic Resonance Imaging (MRI) scans that provide comprehensive data. For the simulation of the model, 50 DICOM files representing multi-frame superimposed brain images that were extracted from the dataset are analyzed to evaluate the proposed design [23-24]. The dataset is accessible at http://braintumorsegmentation.org/.

3.2 Image Pre- processing

This is the foremost step applied after uploading the test tumour image. Here, intensity-based image enhancement technique and contrast enhancement has been performed through limiting. Limiting means that the intensity and contrast of the pixels are increased upto some limit extend. In this step, 'n' dimensional original MRI image is used with known minima and maxima intensity values. In the process, the intensity values of the original image '$Image_{original}$' are modified to a new image '$Image_{New}$.' The conversion to a enhance image is done using the following equation:

$$Image_{New} = \left(Image_{original} - Int_{min}\right)\frac{Int_{NewMax} - Int_{NewMin}}{Int_{Max} - Int_{Min}} + Int_{NewMin} \qquad (1)$$

Where, Int_{Max} *and* Int_{Min} are the lower and higher pixel intensities of the original image and Int_{NewMax} *and* Int_{NewMin} are the modified intensities of the resultant enhanced MRI image $Image_{New}$. Based on the image enhancement approach, we enhance the quality of MRI image that is shown in the below figure 3 with original MRI data.

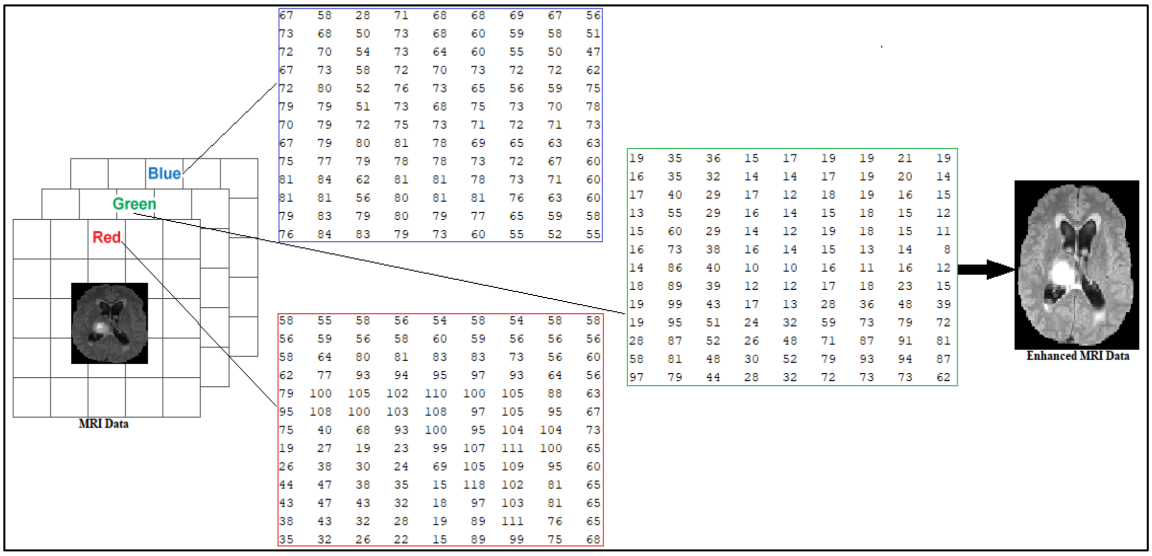


Figure 3. Pre-processing on MRI Data

Image pre-processing technique helps to enhance the quality of the MRI image based on their bands (Red, Green and Blue) so that tumor region segmentation becomes simple and easy to differentiate. Now, we can easily see the exact region of the tumor in the enhanced MRI data with white matter.

3.3 Image Segmentation

The segmentation techniques that are used in this work are performed using two techniques (i) K-means, and (ii) K-means with Optimization Algorithm. The later approach is again sub divided into two techniques (i) K-means with PSO, and (ii) K-means with Firefly Algorithm. These techniques are explained in detail in the following sections. As shown in Figure 4, Image segmentation consists of two images one is Gray scale image and other is colour image. The pre-processed images are first converting into Gray image consisting of three colour levels (Gray, black and white). The colours are assigned as per the intensity level of the pre-processed image that is pixels with minimum and maximum intensity are denoted by the black and the white colour, whereas, the pixels of medium intensity is denoted by the Gray colour (see Table-1). To detect tumour in the gray scale image is very hard, therefore, colour conversion process has been performed to convert gray scale image into color image. After this, K-means, K-means with PSO, and K-means with FA is applied to segment the tumour part of the image. To segment the tumor region, we apply traditional K-means approach only and then with Meta heuristic approaches such as PSO and FA and then analyze their efficiency.

3.3.1 Segmentation using K-means

The clustering issues could be successfully solved with the help of the k-means clustering approach that was proposed by Hartigan and Wong in 1979 [25, 26]. This unsupervised learning approach is applied here for image segmentation to distinguishing the Region-of-Interest (RoI) from the background. The algorithm creates ‘k’ number of clusters from the input pixel set of the image of x×y size, where, x and y are Row and column respectively. Now n(x, y) becomes input pixels to be cluster with the cluster center represented by o. It calculates the smallest distance among the clusters using the following equation:

$$d = || n(x, y) - o_j || \qquad (2)$$

Where d is the distance between each pixel of an image and the center of the cluster "o".

Further, it assigns all the pixels center "o", based on the distance "d". Then once again, it calculates the cluster center by the following equation until stopping criteria are met.

$$f(j) = \sum_{j=1}^{c} \sum_{i=1}^{C} ||n_{(x,y)} - o_j|| \qquad (3)$$

Where f(j) is the objective function, a number of clusters ranging from 1 to "c" and number of cases ranging from 1 to "C". 'C' represents the number of data elements. This function relies on another distance function calculated using the ith case and the jth cluster.

The steps of the algorithm are as follows:

1. Input: $Image_{MRI}$ // Brain tumor MRI scan
2. Calculate: $[Row, Col] = size\ (Image_{MRI})$ // Calculating the size of the image
3. $For_{each}\ i\ in\ Row$
   $For_{each}\ j\ in\ Col$
   Check: $if\ Pix.dist_{i,j} = Forground_{(i,j)}$ // Checking whether the pixel size is equal to the foreground
   $Assign\colon RoI_1 = Forground_{(i,j)}$
   Else: $RoI_2 = Background_{(i,j)}$
   End_{if}
   End_{for}
4. End_{for}
5. $Image_{RoI} = \min(RoI_1 RoI_2)$
6. Output: $Image_{RoI}$ // Tumor Region as RoI

The K-means algorithm works with brain tumor MRI scans as input and identifies the size of the image matrix to separate all pixels into two different groups, such as ROI 1 (foreground) and ROI 2 (background). The preliminary objective is to separate the foreground or the background of the MRI image based on the Euclidean distance between centroid C1 and C2, where C1 and C2 are the means of ROI 1 and ROI 2. Based on the C1 and C2, each pixel is categorized into two categories, which are known as the foreground and background of MRI data. The ground truth of the foreground is matched with the C1 based on their distance, and hence if the pixel value is not equal to the background, then it is the foreground for sure.

The issue with k-means is that it separates the image value only based on the foreground and the background. The foreground and background may have interchanged data that means the data may not be true either for the foreground or for the background because it is based on the exact pixel value, and a pixel value of some portion may be the same. To overcome this issue, the proposed work model evaluates a new behavior for both PSO and Firefly algorithm. The segmented outcomes are shown in Figure 4. It is observed that the foreground data is mixed with back ground data and we got an irregular pattern of tumor. If we used such type of tumor region of feature extraction then we got irrelevant feature set and classification of tumor becomes difficult. So, to solve such type of problem, we utilizing the concept of Meta heuristic approaches such as PSO and FA.

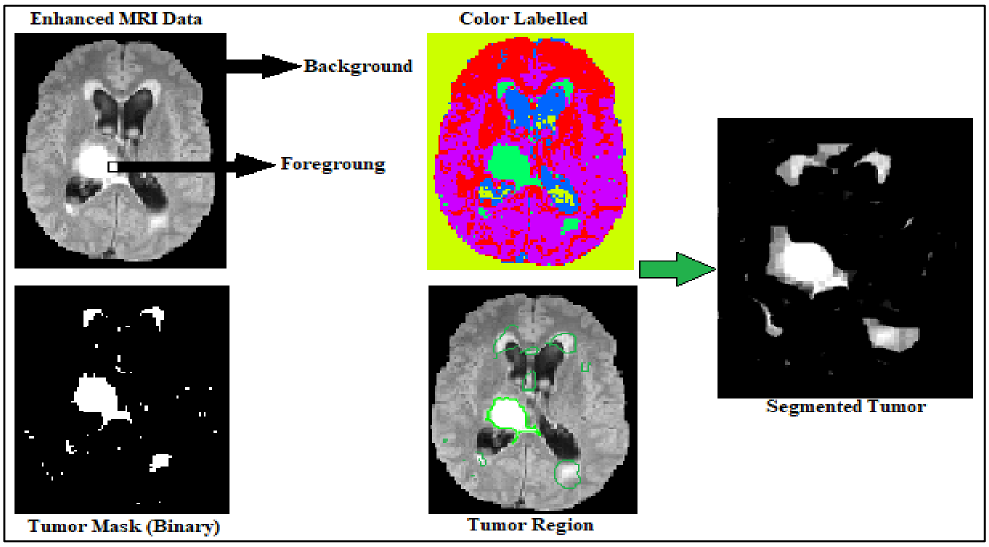


Figure 4. Segmentation using K-means only

3.3.2 Segmentation using K-means with PSO

Particle Swarm Optimization was established by Eberhart and Kennedy as an evolutionary image segmentation technique [27-30]. It possesses machine learning architecture as it has to take decisions based on particles behaviour and architecture. The algorithm is bestowed with the ability to move over the search space and track their coordinates with a fitness solution. PSO is a swarm-based metaheuristic algorithm that is combined with the unsupervised clustering to enhance the image segmentation quality.

Traditionally, in PSO velocity and position is initialized of the ith particle as follows:

$$X_i = (y_{i1}, y_{i2}, \dots \dots y_{iD}) \quad (4)$$

Where y_{iD} represents the D^{th} cluster centroid in solution by ith particle. As such large numbers of candidates are available to swarm.

Fitness of the i^{th} particle is determined as follows:

$$f(j) = \frac{\sum_{j=1}^{C}\sum_{i=1}^{C} ||n_{(x,y)} - o_j||}{N_{x,y}} \quad (5)$$

Where $N_{x,y}$is the numeric value and covers of data points because it is found that the dispersion of the clusters can be minimized by minimizing the fitness function. If (iterations > Itr), the next steps can be escaped. Where 'Itr' is the predefined number of iterations

The position vector of the best swarm particle can be stored by the following equation:

$$v_{iD} = v_{iD} + a_1 * rand()(p_{iD} - x_{iD}) + w_1 * rand()(I_D - x_{iD}) \quad (6)$$

Where i is the index of the best particle in the swarm, v_{iD} is the velocity of the i_{th} particle in the D_{th} dimension.

$$x_{iD} = x_{iD} + v_{iD} \quad (7)$$

If X_{iD} does not lie in D-dimensions, it can be calculated as follows:

$$X_{iD} = (X_{min} \ , X_{max}) \quad (8)$$

This simply defines that for an out of boundary particle, the position, as well as velocity, is calculated using maxima and minima. As a result, the decrease in inertia weight 'W' that controls the impact of the previous velocity of a particle on the current particle is calculated as follows:

$$V_{it} = W * V_{i(t-1)} + K_1 * R_1 * (p_i - x_{i(t-1)}) + K_2 * R_2 * (g_i - x_{i(t-1)}) \quad (9)$$

Where R1 and R2 are independent uniformly distributed random variables, K1 and K2 are acceleration coefficients controlling maximum step size during iterations.

In the proposed methodology, the unsurprised clustered data is combined with PSO for the further refinement of the image quality for accurate detection of tumor Region-of-Interest (RoI). The steps of the combined algorithm are as follows:

Steps in k-means with PSO Algorithm

1. Input: $Image_{MRI}$ // Brain tumor MRI scan
2. Calculate:
   $[R, C, P] = size(Image_{MRI})$ //identify rows, columns and plane of MRI
3. $Image_{MRI} = double(Image_{MRI})$
4. $Assign\ variable$:
   $P_{parts} = 2$ //number of parts for k-means also known as the centroid
5. $Index_{Simg} = kmeans(Image_{MRI}, P_{parts})$ // Apply K-means
6. $Label_{Simg} = reshape(Index_{Simg}, R, C)$ // Labelling through k-means which represents the pixel categories and it should be in 1 or 2 group

7. $Pos_{data} = find(Label_{Simg} > 0)$ // Evaluating the non-zero elements as only the non-zero element will contain the pixel value
8. $Data_{img} = Label_{SCimg}(Pos_{data})$ // Labelling the non-zero elements
   / The non-zero elements are to be rectified in order to appropriately classify the background and the foreground of the image
9. $Initialize\ PSO\ parameters$ // Initials of the PSO are to be justified as follows
10. $For_{each}\ pixel\ value$ in foreground (FG)and the background (BG)$PSO_{particle} = pixel_{value}$
    $If\ pixel_{value} lies\ in\ background$
    $Velocity = \sum_{i=1}^{s} \frac{Foreground}{s}$ // where s is the total number of pixels in foreground
    $Allowed_{Velocity} = Velocity * Speed_{Variation}$
    where $Speed_{variation} is\ random$
    $Else$
    $Velocity = \sum_{i=1}^{k} \frac{Background}{k}$ // where k is total number of pixels in background
    $f_{fit} = \begin{cases} 1\ ; & if\ PSO_{particle} * Velcoity < Allowed_{velocity} \\ 0\ ; & otherwise \end{cases}$
    End_{if}
11. End_{For}
12. $For_{each}\ nonfit$ pixel
    $If\ Pixel.base\ value\ is\ the\ foreground$
    $Segmented\ Region$ = Shift to Background
    $\boldsymbol{End_{if}}$
    $Segmented\ Image = MR\ Image * Segmented\ Region$
13. End_{for}
14. **Return**:
    $Segmented\ Image\ as\ ROI\ of\ Brain\ Tumour$

The PSO algorithm takes each pixel value in the background and the foreground and analyses it separately. The proposed algorithm introduces a behavior of random speed in between the particles. The fitness function of the PSO algorithm takes the allowed velocity as the input parameter along with the PSO particle and its associated velocity. The PSO particle is termed to be the pixel value of the foreground or the background in separate cases. The velocity of each class is the average ground-truth value of the class. The segmentation output of K-means with PSO is shown in the below figure 5.

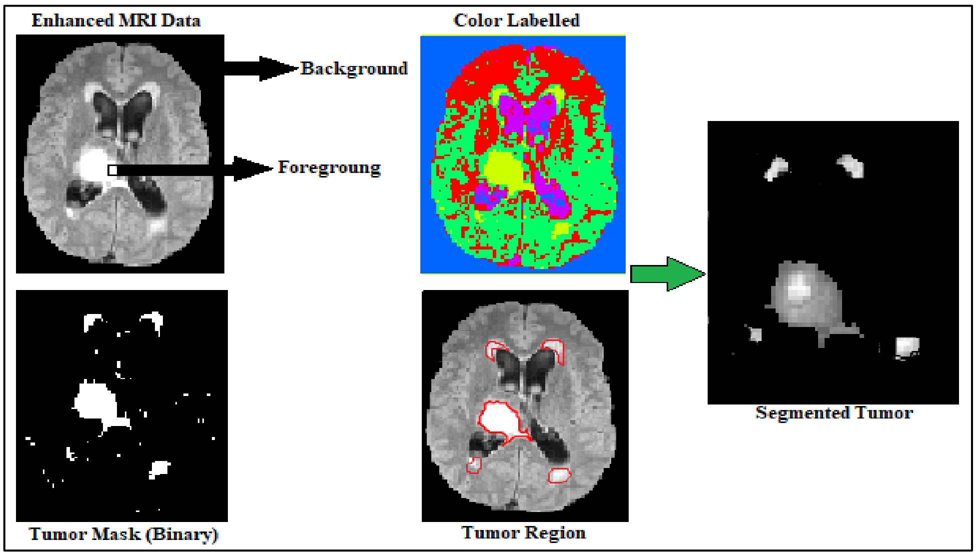


Figure 5. Segmentation using K-means with PSO

By utilizing the PSO with morphological operations, we obtained a better segmented out that is clearly visible in the figure. It clear that the mix-up problem of the foreground is mixed with background data is reduced but not up to acceptance, so we utilizing the concept of FA as a Meta heuristic approach to solve this problem.

3.3.3 Segmentation using K-means with FA

The FA is a nature-inspired algorithm the same as that of above defined PSO algorithm. The algorithm is inspired by the attractive behaviors of Fireflies and was developed by Yang in 2010. Since 2010, the FA algorithm has been used successfully in numerous applications to solve various optimization problems. Using FA, by performing the iterative process, a new solution is generated on the basis of preceding results. The coverage range is decided based on the attraction behavior of fireflies. The output with the best fitness function value is selected [31]. The quality of the optimized pixel is calculated using the fitness function of FA, which is written by equation (10)

$$f\ (fit) = \begin{cases} 1 & if\ a\ pixel\ is\ less \\ 0 & otherwise \end{cases} \quad (10)$$

The best solution selection depends upon the movement of flies towards a better solution. Therefore, the attractiveness between the two solutions is calculated using equation (11);

$$\beta(d) = \frac{\beta_0}{1+Kd^2} \quad (11)$$

Where β_0 is the attractiveness distance at distance d=0, K is the constant of proportionality?

Algorithm: K-means with FFA

1. $Input$: $MR\ Image \rightarrow Brain\ Tumour\ MRI\ Data$
2. $Output$: $ROI \rightarrow Tumour\ ROI\ Image$
3. $[R, C, P] = size\ (MR\ Image)$
4. $MR\ Image = double\ (MR\ Image)$
5. $Number\ of\ Part = 2$
6. $SimgIndex = kmeans\ (MR\ Image, Number\ of\ Part)$
7. $SegLabelImg = reshape\ (SimgIndex, R, C)$
8. $DataPos = find\ (SegLabelImg > 0)$
9. $Data = SegLabelImg(DataPos)$
10. $Initialize\ FFA\ parameter - Iterations\ (itr)$
    - $Population\ Size\ (S)$
    - $Lower\ Bound\ (LB)$
    - $Upper\ Bound\ (UB)$
    - $Fitness\ function$
    - $Number\ of\ selection\ (N)$
11. $Calculate\ T = Size\ (MR\ Image)$
12. $Fitness\ function$:
13. $f\ (fit) = \begin{cases} 1 & if\ f_s \le f_t \\ 0 & otherwise \end{cases}$
14. $For\ 1 \rightarrow size\ T\ with\ respect\ to\ i$

    $$fs = \sum_{i=1}^{S} Data(i)$$

    $$ft = \frac{\sum_{i=1}^{S} Data(i)}{Length\ of\ feature}$$

    $f(fit) = fitness\ function$ which is defined by the above given equation

    $Threshold_{value} = FFA(S, itr, LB, UB, N, f(fit))$
15. End_{for}
16. $While\ itr \sim= Maximum$

    $Threshold = Threshold_{value}$

    $MaskImg = Morphological\ (SimgIndex, Threshold)$

    $Boundaries = bwboundaries\ (MaskImg)$

    $Segmented\ Region = Boundaries$

    $For\ i \rightarrow 1: P$

    $Segmented\ Image = MR\ Image * Segmented\ Region$

    End_{for}
17. End_{while}
18. *Return: Segmented Image as ROI of Brain Tumour*

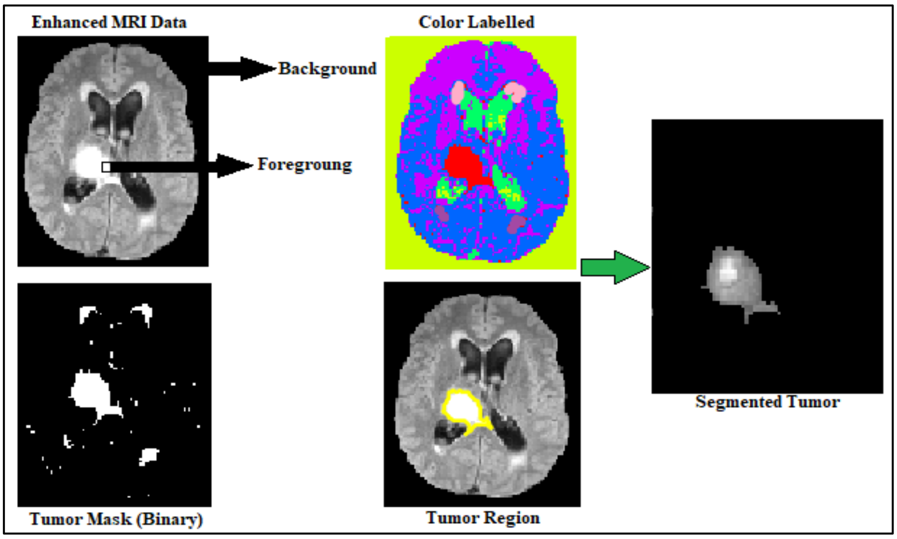


Figure 6. Segmentation using K-means with FA

FA works in a similar manner as that of PSO. Both FA and PSO are the swarm intelligence techniques and used for the threshold selection using the fitness function, but PSO consider only three factors (position, distance, and velocity of particles) during the optimization process whether FA used four factors (position, distance, light intensity and velocity of particles) during the optimization process. Due to more factor consideration, FA provides a better and optimistic result compare to the PSO, which are also proved by the experimental analysis in the result section.

4. Result

The segmentation results obtained for the three test MRI scans are shown in Table 1, Table 2, and Table 3. Table 1 summarizes the step by step changes in the image visualization starting from the original uploaded image to the extracted RoI during the image segmentation performed using k-means. The same test images have also been evaluated for k-means with PSO and FA combinations.

The tumor image segmentation results for the three test images, namely, Test Image 1, Test Image 2, and Test Image 3, with the proposed combination of k-means with FA, are shown in Table 3. Comparing the column 6 of Table 1, Table 2 and Table 3, it is observed that the RoI of the segmented image obtained as a result of the combination of K-means with FA is much better for all the test images. The tumor region in the segmented images in column 6 of Table 3 is more precisely marked, concluding it to be the best among the three for brain tumor image segmentation

Table 1. Image Segmentation using k-means

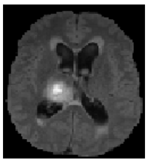
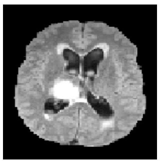
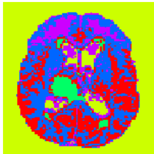
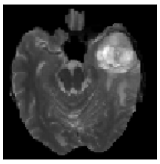
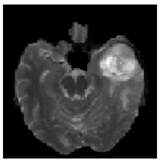
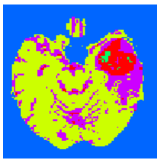
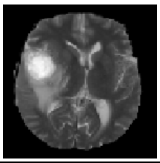
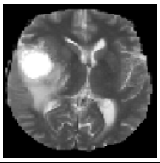
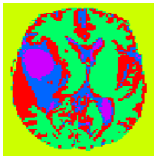
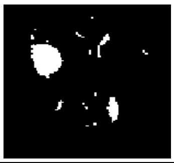
Sample MRI Image	Original Image	Enhanced Image	Grey Labeled	Color Labeled	Segmented Image
Test Image 1					
Test Image 2					
Test Image 3					

Table 2. Image Segmentation using k-means with PSO

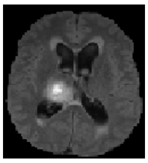
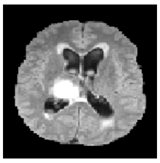
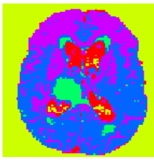
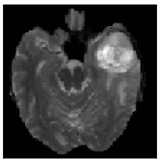
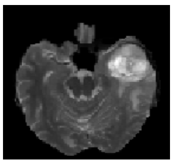
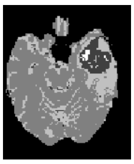
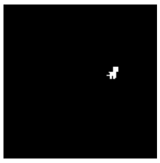
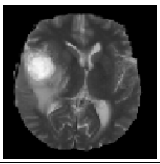
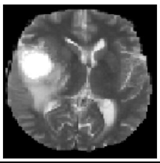
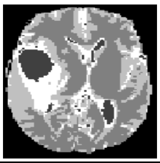
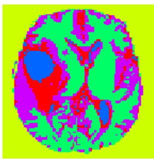
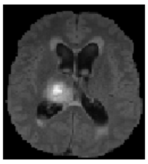
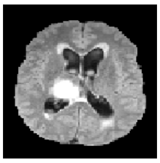
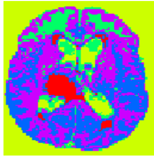
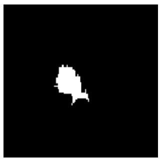
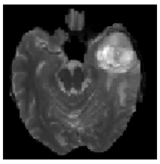
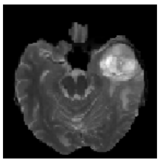
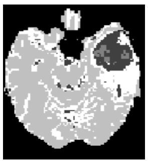
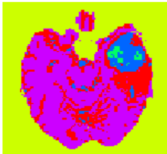
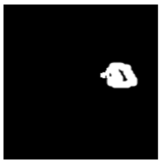
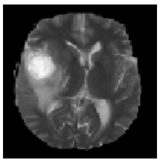
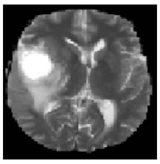
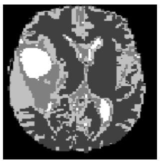
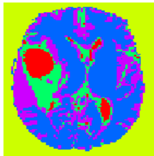
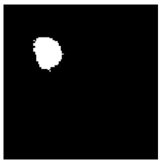
Sample MRI Image	Original Image	Enhanced Image	Grey Labeled	Color Labeled	Segmented Image
Test Image 1					
Test Image 2					
Test Image 3					

Table 3. Image Segmentation using k-means with Firefly Algorithm

Sample MRI Image	Original Image	Enhanced Image	Grey Labeled	Color Labeled	Segmented Image
Test Image 1					
Test Image 2					
Test Image 3					

The program is designed in MATLAB 2016 with an intel core i3 processor, and 2GB RAM. To show the effectiveness of the proposed work comparison of proposed work with existing segmentation approach is provided for the same dataset. To evaluate the performance parameters such as Precision, Recall, F-measure, and Accuracy are calculated to evaluate the performance of designed model using the following formulas:

$$Precision = \frac{True_{Positive}}{True_{Positive}+False_{Positive}} \tag{11}$$

$$Recall = \frac{True_{Positive}}{True_{Positive}+False_{Negative}} \tag{12}$$

$$F_{measure} = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{13}$$

$$Accuracy = \frac{True_{Positive}+True_{Negative}}{True_{Positive}+True_{Negative}+False_{Positive}+False_{Negative}} \tag{14}$$

Initially, the experiments are performed on dataset with 10 number of image samples and analysed the performance parameters. The images are uploaded randomly from the dataset, and the observed values of precision, recall, F-measure, accuracy and time taken by the system to segment image has been evaluated.

The results calculated using the above formula are summarized in Table 4 and Table 5. In Table 4, values of precision, recall, and f-measure are listed to compare the results obtained using k-means and k-means combination with PSO and FA. It is observed that precision values for k-means lie between 0.83 and 0.88 for k-means with PSO. It lies between 0.86 and 0.95, and for k-means with FA, it lies between 0.92 and 0.99. A similar trend is followed by recall and f-measure.

Table 4. Precision, Recall, and F-measure obtained using k-means, k-means with PSO and k-means with FA

Number of Image Samples	K-means			k-means with PSO			K-means with FA		
	Precision	Recall	F-measure	Precision	Recall	F-measure	Precision	Recall	F-measure
1	0.835	0.643	0.727	0.863	0.825	0.844	0.927	0.894	0.911
2	0.845	0.738	0.788	0.885	0.838	0.861	0.957	0.908	0.932
3	0.856	0.797	0.826	0.873	0.849	0.861	0.973	0.901	0.936
4	0.865	0.781	0.821	0.908	0.827	0.866	0.958	0.915	0.937
5	0.846	0.815	0.831	0.895	0.847	0.871	0.991	0.978	0.985
6	0.886	0.818	0.851	0.908	0.826	0.866	0.968	0.928	0.948
7	0.854	0.801	0.827	0.951	0.859	0.903	0.968	0.945	0.957
8	0.875	0.835	0.855	0.927	0.869	0.898	0.995	0.997	0.996
9	0.856	0.825	0.841	0.959	0.883	0.92	0.978	0.963	0.971
10	0.865	0.836	0.851	0.925	0.834	0.878	0.989	0.983	0.986

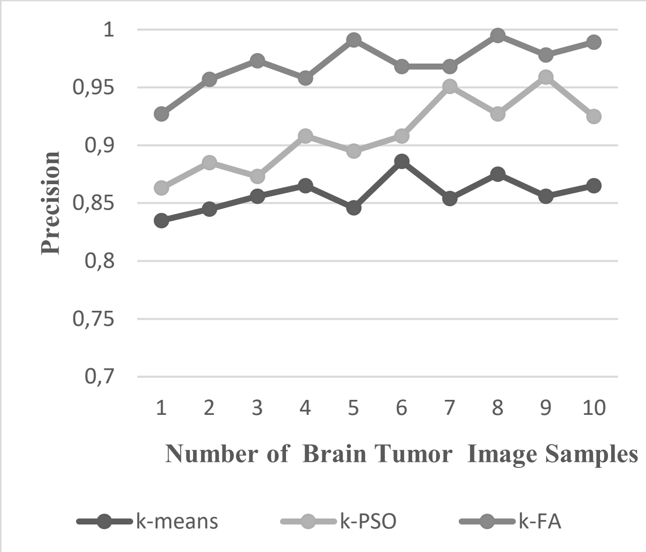


Figure 7. Precision

Figure 7 represents the comparison of precision results for k-means, k-means with PSO, and k-means with FA. In the graph, a number of brain tumor images is plotted on the X-axis against the parametric values of precision for all the three cases. The average precision of brain tumor segmentation using k-means is 0.86, k-means with PSO is 0.91 and k-means with FA is 0.98. It is observed from the graph that the highest precision is obtained for RoI detection using k-means with FA as compared to k-means with PSO or alone k-means as segmentation techniques. Hence, it is concluded that k-means combined with FA provided the best results by segmenting the relevant area of brain tumors to a larger extent as compared to the others.

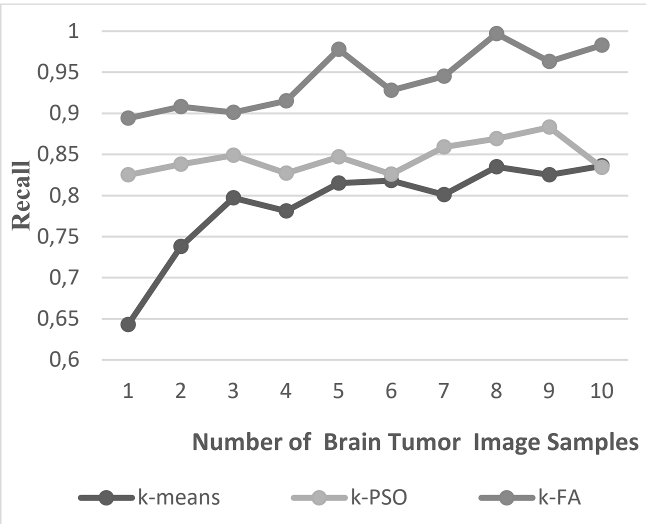


Figure 8. Recall

Recall values correspond to the sensitivity of the obtained results and are used for the evaluation of the segmentation techniques employed for brain tumor RoI detection. Figure 8 corresponds to the graph for the number of brain tumor images plotted against the recall values obtained using the three approaches. The recall value obtained using k-means falls in the range of 0.643 and 0.835, with an average value of 0.79. Similarly, recall value using k-means with PSO lies in the range of 0.825 and 0.883, with an average value of 0.85. It is observed that using k-means with FA range of recall values rises and lie between 0.894 and 0.997 with an average value of 0.95. This shows that using FA with k-means increases the strength of image segmentation by increasing the extent of detection of the more relevant region in the sampled brain tumour images.

Figure 9 shows the effectiveness of the applied algorithms in terms of a number of brain tumor images plotted against the f-measure values. It is observed that for the f-measure obtained using k-means with PSO is higher than that obtained using k-means alone. Similarly, f-measure obtained using k-means with FA is further higher than that obtained using k-means with PSO. The average value observed for f-measure using k-means with FA, k-means with FA and k-means is 0.96, 0.88, and 0.83 for, respectively. This shows that k-means with FA is more effective in the retrieval of the tumor RoI as compared to k-means with PSO and k-means.

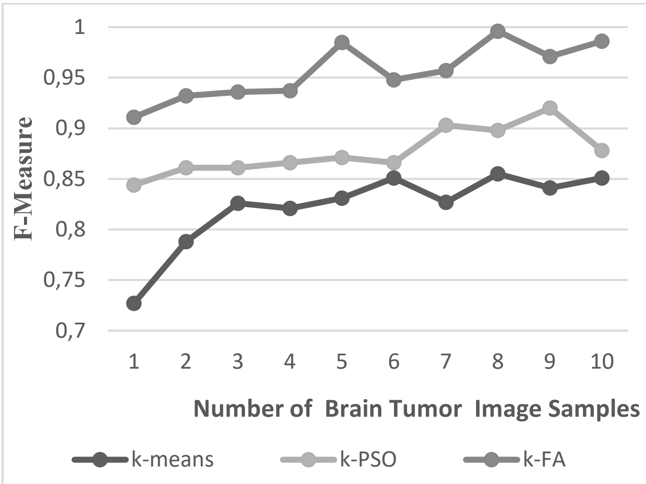


Figure 9. F-measure

The parametric values of observed accuracy and segmentation time required for processing using k-means, k-means with PSO, and k-means with FA are tabulated in Table 5. It can be observed that accuracy values are higher for k-means with FA with lower segmentation time as compared to other approaches. A more comprehensive comparison of the resultant values is shown in Figure 10 and Figure 11.

Table 5. Accuracy and Segmentation time comparison obtained using k-means, k-means with PSO and k-means with FA

No. of Image Samples	K-means		k-means with PSO		k-means with FA	
	Accuracy (%)	Time (sec)	Accuracy (%)	Time (sec)	Accuracy (%)	Time (sec)
1	82.54	3.58	88.67	8.57	95.28	5.85
2	83.46	4.87	89.43	9.65	96.18	6.45
3	85.67	3.98	91.78	10.86	96.58	7.56
4	85.05	4.87	90.97	10.97	99.12	8.64
5	86.34	5.35	92.36	9.87	97.37	7.86
6	85.27	4.98	95.43	11.54	98.28	7.12
7	86.23	3.96	93.28	10.54	97.74	8.47
8	87.67	4.23	93.62	11.86	98.29	8.15
9	86.27	4.68	94.23	10.14	99.13	8.97
10	87.28	4.79	95.42	8.28	99.47	6.86

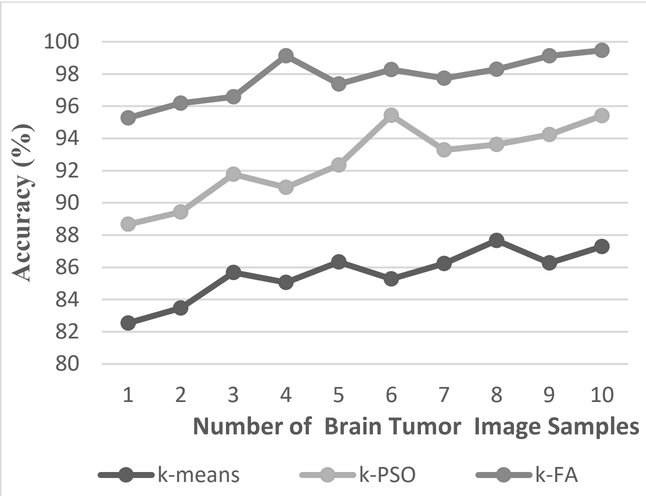


Figure 10. Accuracy

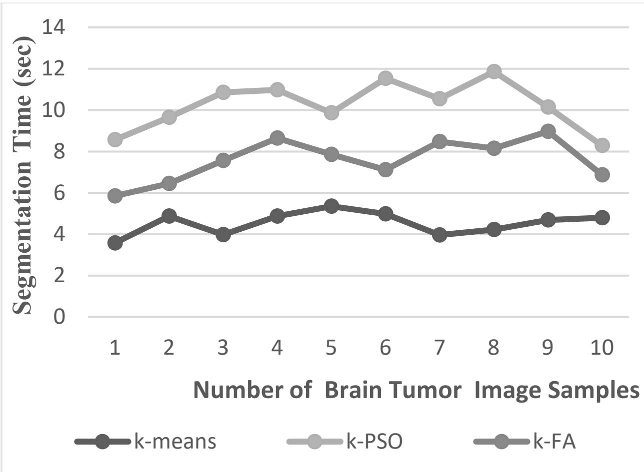


Figure 11. Segmentation Time

Figure 10 compares the accuracy of the segmentation results for the 10 sample brain tumor images using k-means, k-means with PSO, and k-means with FA. In the case of the 10 brain tumor image samples, the accuracy of segmentation using k-means lie between 82.54% and 87.67%, using k-means with PSO, it lies between 88.67% and 95.42% and using k-means with FA it lies between 95.28% and 99.47%. This can be summarized to an average accuracy of 85.58%, 92.52%, and 97.75% observed using k-means, k-means with PSO, and k-means with FA, respectively. The graph shows that the tumor image segmentation has been more correctly done to detect the tumor region using k-means with FA. An enhanced segmentation accuracy of 12.17% is observed for k-means with FA when compared to k-means alone that is further higher than 5.23% when compared to k-means with PSO.

In the evaluation process, the segmentation time required to complete the image segmentation process has also been computed. Figure 11 represents the graph of a number of brain tumor image samples plotted against the segmentation time utilized to complete the image segmentation process using k-means, k-means with PSO, and k-means with FA. The average segmentation time required to complete the segmentation process of 10 brain tumor image samples is 4.53secs using k-means that get increased to 7.6secs and 10.23secs by combining k-means with FA and PSO, respectively. It is observed that on an average k-means combination with FA took 2.63secs less than the combination of k-means with PSO. Hence, k-means with FA is found to be less time consuming with more relevant results. Among the presented image segmentation approaches such as K-means, K-means with PSO, and K-means with FA, the last one performs better against the two approaches.

5. Conclusion

In this paper, the quality of image segmentation for brain tumor MRI scans is evaluated using three approaches, namely, k-means, k-means combined with PSO, and k-means combined with FA. The new behavior of velocity variation is introduced in the existing architecture of both PSO and Firefly algorithms. In the proposed framework, color and gray labeling techniques have also been employed to improve image segmentation results and RoI extraction. With a perfect mechanism and strong, soft tissue imaging, patients can be diagnosed scientifically by using the new segmentation methods. It enables doctors to grasp the exact progress of the disease state that helps to make decisions about proper treatment, surgery, and follow-up for disease and hence accordingly provide control measures. The proposed approach reduces the doctor's workload and enhances the detection accuracy of the medical analysis. The performance of the proposed framework is evaluated in terms of parametric values of precision, accuracy, f-measure, recall, and segmentation time. Average recall and f-measure of 0.95 and 0.96 are obtained for the combination of k-means with FA and 0.85, and 0.88 is observed for k-means with PSO. The performance evaluation results show that an average accuracy of 97.75% with 98% precision is obtained when k-means is combined FA. Enhanced accuracy of 5.23% is observed with k-means hybrid with FA in comparison to k-means hybrid with PSO. Additionally, image segmentation using k-means with FA took 2.63secs less than using k-means with PSO.

Overall, it is observed that the tumor RoI has been more precisely and accurately segmented using the combination of k-means with FA while consuming lesser segmentation time when compared with k-means with PSO. Hence, it is concluded that k-means combination with FA is better than the others for brain tumour image segmentation.

In future, the work can be extended by including more features, which can help to enhance the detection accuracy.

The tumor ROI segmentation accuracy of the proposed brain tumor segmentation model is high but segmentation time still high and it should be minimized in the future by combining K-means as machine learning approaches with swarm-based meta-heuristic algorithms.

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