Bulletin of Environment, Pharmacology and Life Sciences
Bull. Env. Pharmacol. Life Sci., Special Issue [1]2022 : 440-458

Online ISSN 2277-1808
Journal's URL:http://www.bepls.com
CODEN: BEPLAD
REVIEW ARTICLE **OPEN ACCESS**

Automatic segmentation of Brain tumour using improved clustering mechanism

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ABSTRACT
Digital image processing approach contributions increase day by day in human life and it becomes an emerging research field in biological sciences for a lot of medical applications such as brain tumour detection and classification, blood cancer detection and classification, and testing as well as examining critical parts of the human body using the x-ray or microscopic images. In the last decades, lots of researchers are interested in the development of an Automatic Segmentation of Brain Tumour (ASBT) system for segmentation of tumour and Region of Interest (ROI) from the brain MRI images. The proposed technique of segmentation is focused on the division of white matter and grey matter into background and foreground that is known as Region of interest (ROI) of tumour. There are lots of traditional clustering-based techniques available for the segmentation of the tumour but all algorithms had faced pixel mixed up problem. So, the present work has developed an ASBT system for the tumour segmentation from the MRI images by developing six different techniques such as Fuzzy C-means (FCM), K-means, FCM with Particle Swarm Optimization (PSO), K-means with PSO, FCM with Grasshopper Optimization Algorithm (GOA) and K-means with GOA. After that, we found the better approach of tumour segmentation from MRI based on the comparison of segmentation performance parameters like accuracy, sensitivity, F-measure, precision, mcc, dice, Jaccard, specificity, and time complexity. The segmentation accuracy of the proposed ASBT system with six different scenarios is evaluated to validate the model on the BraTS MRI image dataset by comparing with the rest of all techniques as the well existing state of arts. From the experimental analysis, we observed that the segmentation accuracy of the ASBT system using the K-means with GOA is better than others and it is more than 99% for most of the MRI sample images.In addition, the model with the combination of K-means and GOA as an optimization algorithm segments the ROI of tumour from the human brain MRI image within a very short time period in few seconds compared to other approaches
Keywords: Cancer, Brain Tumour, Image segmentation, CNN, K-means, PSO, GOA and MRI Images

Received 12.03.2022 Revised 27.03.2022 Accepted 04.04.2022

INTRODUCTION

In human body, when abnormal cells are generated in an uncontrolled way then it converts into brain tumour and these are categorised into two type named as:

1. Benign: It is a noncancerous type of brain tumours and the formation is very slow due to which it is less aggressive. This type of tumours does not spread to another region of the brain as well as other parts of the human body.
2. Malignant: It is a cancerous type of brain tumour and not always easy to differentiate from nearby normal tissues in the brain. So, the extraction or segmentation of these types of tumours is not easy without damaging the adjacent tissues of the human brain.

It is the 2nd leading cause of death globally with 8.8 million cancer related deaths worldwide in 2015, annual no. of new cases is projected to rise from 14.1 million in 2012 to 21.6 million in 2030. According to the American Cancer Society (ACS), the number of affected humans by malignant types of brain tumours has been esclating in the last few decades in the world [1].The researchers need attention in the diagnosis of a brain tumour in early-stage or benign stage, so that it may be curable based on the Computer-Aided Design (CAD) analysis because an automated brain tumour diagnosing has been fascinated the attention of numerous pathologists in research as well as clinic practicing that helps to reduce human error, false-positive results, and time intricacy of the model using Magnetic Resonance Imaging (MRI) technique [2]. A number of image capturing techniques are existing such as MRI scan, CT (Computed Tomography) scan, PET (Positron Emission Tomography) scan, Angiography etc., but in this research, we used the MRI scan data for the comparative evaluation of the existing tumour segmentation approaches with the proposed improved clustering-based approaches [3].Because it is a non-invasive medical imaging modality frequently utilized in the clinical routine as it offers images by means of giant spatial resolution and high contrast between soft tissues. Also, MRI scan data provides a good set of information about tumour like their shape, size, and localization of the brain that may help in diagnosis and treatment planning of brain tumours in the early stage [4]. The sample of brain tumour images for healthy and brain with a tumour is shown in Fig. 1 and we can easily segregate the types of tumours.

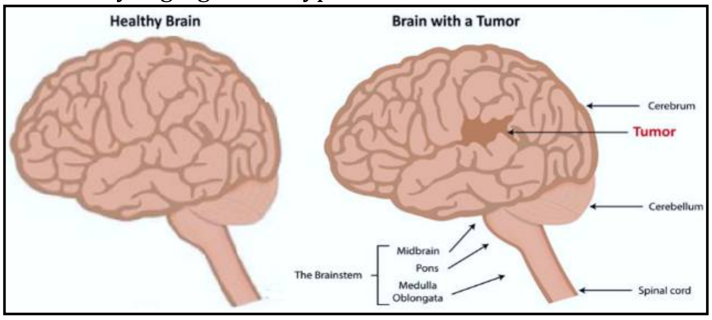


Fig. 1: Healthy and Brain with Tumour

The automatic segmentation of brain tumour from MRI images is an emerging practice concerning computer-assisted pathology and their main aims to provide fast and robust diagnosis decisions based on the digital image segmentation approaches [5]. At present, automated brain tumour or other types of tumours has been fascinated the attention of numerous pathologists in research and clinic practicing.

However, there are some problems, such as this process which takes a great amount of time for analysis, and the results of the MRI imaging may vary depending on the technique or technology. In addition, the results of diagnostic tests for brain symptoms may vary under different conditions by the same physician, and the brightness and contrast of the display screen may vary with the results of classification [6]. For these reasons, the selection of spontaneous classification of brain tumors becomes an important factor in the classification of primary stage tumors. Brain tumour segmentation using MRI images plays vital role in numerous applications in neurology that involve precise estimation of tumour size, tumour location, tumour volume, lesions, blood cells demarcation, therapy, and surgical planning [9]. A MRI image of the brain consists of White matter (WM), Grey Matter (GM), and Cerebrospinal Fluid (CSF) filled cavity as shown in Fig. 2.

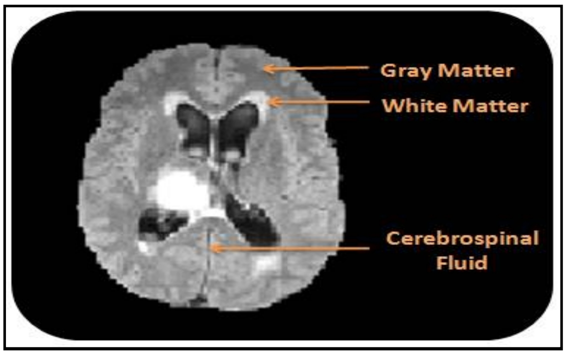


Fig. 2: MRI Scan of Human Brain

In this so, we presented a comparative analysis of the Automatic Segmentation of Brain Tumour (ASBT) system from MRI images using the clustering approaches namely Fuzzy C-means (FCM) and K-means with hybridization swarm-based optimization technique such as Particle swarm optimization (PSO) and Grasshopper Optimization Algorithm (GOA).We present a comparative brain tumours segmentation model using clustering-based methods and their hybridization with swarm-based optimization approaches and the block diagram of the proposed ASBT model is shown in Fig. 3.

The ASBT system is implemented to improve the segmentation efficiency because in the existing work, segmentation of white matter (foreground) and grey matter (background) was done based on traditional segmentation techniques but they do not cover the error minimization during the segmentation of tumour region from the MRI images in form of foreground and background. The classification accuracy of a brain tumour detection model depends on the segmentation accuracy, if segmentation is appropriate, then the classification becomes more accurate. In this section of the research article, we introduce the basic idea about brain tumour segmentation from the MRI images and the remaining work is organized as follows: the related work survey is presented in Sect. 2 regarding brain tumour segmentation using MRI images is presented. Where the method and materials of the proposed comparative ASBT system are presented in the Sect. 3 and in Sect. 4, the outcomes and analysis are presented. The overall conclusion of this research is described in the Sect. 5, with the future possibilities about the automatic brain tumour segmentation.

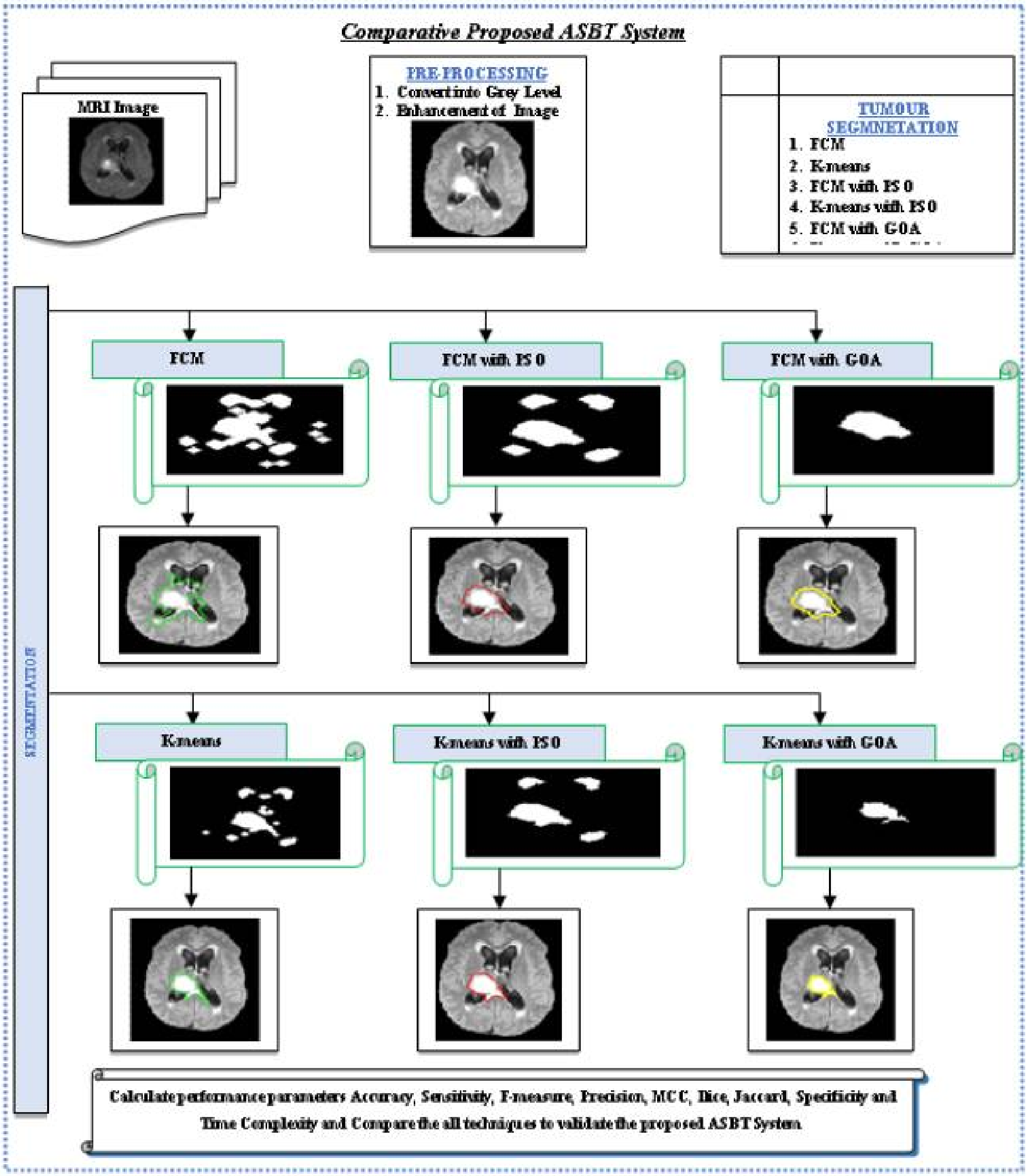


Fig.3: Proposed ASBT System Block Diagram

The first brain tumour segmentation work was proposed in 2004 using the concept of image processing by Derraz et al. and they focused on the improvement of medical diagnosis aided with improved brain tumour segmentation from MRI scan images. They achieved desirable results using the mathematical algorithms for model designing with feature extraction approach and measurement were employed to identify the diseased or abnormal regions in comparison to the normal ones [10]. After that in 2011, Chander et al. worked on the improvements in the segmentation by modifying it using the concept of swarm-based conventional PSO (Particle Swarm Optimization) approach and also achieved improved results in the segmentation accuracy. The experimental evaluation stated that the proposed modified PSO performed well in comparison to the existing segmentation variants and could successfully deal with the segmentation of brain tumour issues. It was also observed that the proposed modified PSO was better than Gaussian smoothing algorithm [11].

They observed that the K-means are applied in most of the research articles when it comes to the initial segmentation procedure. So, in 2019, M. S. Alam et al. designed an automatic brain tumour detection (ABTD) from the MRI images using the concept of K-means and improved FCM as a clustering algorithm.

In this work, they proposed an ABTD model that included two different approaches first is the template-based K-means and the second uses the improved FCM algorithm for detecting human brain tumours from MRI images. First they used a template-based K-Mean algorithm to implement high-level classification by template selection, based on the image depth of the foundation; secondly, renewed membership is determined by distances from cluster centroid to data points using the FCM algorithm while communicating its best result, and finally, an improved FCM algorithm is used to locate the tumor by reviving the acquired membership function based on various aspects of tumor imagery including Contpar, Energy, Dissimilarity, Homogeneity, Entropy, and Correlation. They find better diagnosis of abnormal and normal uterine tissue in MRI scans and also helps to reduce the detection time compared to minutes with other algorithms but segmentation accuracy is needed improvement for better feature extraction [12].

Bousselham *et al.* in 2019, had researched the reinforced brain tumour segmentation from the human brain MRI images based on temperature changes in the pathologic area. The main purpose of this study is to address the thermal knowledge of brain tumors which helps to reduce pixel false positives both positive and negative on the human brain MRI images. Pennies' bioheat equation was used to solve the temperature distribution problem in the brain and also canny edge detector was used to identify tumour contours from the calculated thermal map, as the calculated temperature presented a great gradient in tumour contours [13]. So, to focus on the tumour region segmentation, S. Mahalakshmi et al. in 2015, was used the concept PSO. They analyze the detection and separation of brain tumour from the human brain MRI images using The PSO as a heuristic global optimization approach is based on swarm intelligence. The whole work is divided into four categories which include execution, selection, conversion, and extraction [14].

The work also identifies the best suitable plane for the PSO algorithm for segmentation but needs to improve the problem-solving time and S. Saremi *et al.* in 2017 developed a new problem-solving optimization approach that is known as Grasshopper Optimization Algorithm (GOA). The proposed swarm-based improvisation of PSO that known as the GOA algorithm and it is a mathematically models and mimics the behavior of grasshopper in nature for solving optimization problems and also helps to minimize the problem of traditional segmentation approaches like K-means, FCM, etc. [15]. Recently in 2020, M. C. Trivedi et al. had conducted research to segment the tumor region from the brain magnetic resonance imaging using Otsu K-means (OKM) method. They present a hybrid approach for the segmentation using Otsu segmentation along with the K-means and give a name as OKM. Here, Otsu thresholding is a threshold-based approach and K-means is unsupervised clustering approach, so OKM also face the mixed upr problem. MRI modalities, which are considered for generating tumor masks is used in this research, for the BRATS dataset. The experimental results of research is satisfactory but obtained dice coefficient need to boost up and also it does not involve training and large size databases [16]. Related to this work, in 2019, R. Pitchai et al. proposed an automatic segmentation of brain tumor from the MRI image using the Fuzzy K-Means Clustering approach along with Deep Learning. Authors use the concept of Artificial Neural Network (ANN) as a deep learning approach along with the Fuzzy K-means algorithm to segment the tumor region available in the MRI image. The total procedure of this research is categoried into four different phases namsed as denoising, tumour feature extraction, tumor region classification and segmentation of tumour region. ANN based tumour region classification has been performed perfectly then Fuzzy K-Means algorithm is used to segment the brain tumor region from the MRI images. Author used BRATS dataset for the verification of the system efficiency and achieve a good accuracy of 94% but in medical science that need to maximize. So, after studying existing research in the area of brain tumour region segmentation or detection, we observed following inference drowns:

- ❖ Used pre-processing in the existing works cannot provide better normalized MRI images that help in segmentation, so the false point rate is maximum during the tumour region segmentation. These types of problems can be solved by utilizing the limited contrast approach as an image quality enhancement technique.
- ❖ Only the clustering-based segmentation approach is not enough for the medical MRI images segmentation that may be used in the classification purpose of tumour in the human brain.
- ❖ In lots of work, unsupervised clustering approaches such as K-means FCM, etc. are used and so segmentation cannot perform superior on the MRI images in the grey level.

Based on the above-mentioned literate survey, we conclude some important points regarding the segmentation of the brain tumour region from the MRI image which supports to sort out the existing problem in the proposed comparative ASBT system. Initially, we initiate a completely automated hybrid technique for brain tumor region segmentation that is knowns as Region of Interest (ROI) by using six deferent scenarios and compare with each other's scenario in the next section of this research article.

MATERIAL AND METHODS

In this section, we describe the procedural and working steps of the proposed ASBT system for the segmentation of brain tumour from the MRI images. The used material and method for the proposed ASBT system are explained with the properly used algorithm of FCM, K-means, and their hybridization with PSO and GOA. The used steps of the proposed model is described in the below section with explanation of used dataset. BraTS Dataset: For the simulation of the proposed brain tumor segmentation using traditional segmentation approach with meta heuristic techniques, we used a MRI Dataset of 3064 images with three different tumor types such as Meningioma (708 images), Glioma (1426 image), and Pituitary tumor (930 images). Basically, Meningioma and Pituitary tumors are benign types of tumor but Glioma is malignant type of brain tumor. The MRI data is collected in form of DICOM file and then converted into image with png format and acquired from two different hospital named as Nanfang and General Hospital, Tianjin Medical University (TMU), China. All data are labelled as 1 for meningioma, 2 for glioma, 3 for pituitary tumor with patient ID and sample of dataset is given in the Fig. 11. On this MRI image, we performed same pre-processing steps in all comparative models ASBT system:

Pre-processing of ASBT System: In this phase, we use some pre-processing steps in all of the six scenarios of proposed ASBT system, first is the color conversion of MRI image if requirements using the written equation 1:

$$\boldsymbol{GMRI_{Image}} = \boldsymbol{0.3R + 0.59G + 0.115B(} \ (1)$$

Where, GMRI Image is the grey level MRI image that is obtained after the color conversion of the grey level mapping initiated on the clipped region of MRI image for quality enhancement and the average number of pixels in the MRI image described by the equation 2.

$$\boldsymbol{PX_{avg}} = \frac{\boldsymbol{PX_{(reg-x\_axis)}} \times \boldsymbol{PX_{(reg-x\_axis)}}}{\boldsymbol{GMRI_{Image}}} \qquad (2)$$

Equation 2 defines the average number of pixels in the MRI image. Where $P_{(reg-x\_axis)}$ signifies the number of pixels along the x-axis in a clipped region (PCLIP). The clip limit (PCL) of MRI image enhancement is calculated using equation 3 then we apply the image enhancement of further processing using the written algorithm:

Algorithm 1: Image Enhancement Algorithm

Input: MRI Images → MRI-Image
Output: Enhanced MRI Image → EMRI-Image
Start enhancement
Set clip limit, $P_{CL} = P_{CLIP} - P_{AVERAGE}$**(3)**
Calculate the size of MRI-Image = [Row, Col., and D]
If D>1
MRI_R=Red Part of MRI-image
MRI_G= Green Part of MRI-image
MRI_B= Blue Part of MRI-image
For I=1→ Clip Limit
Red = Intensity (MRI_R, P_{CL})
Green = Intensity (MRI_G, P_{CL})
Blue = Intensity (MRI_B, P_{CL})
End – For
EMRI Image = cat (3, Red, Green, Blue)
Else
For I=1→ Clip Limit
EMRI Image = Intensity (MRI (I), P_{CL})
End – For
End – If
Return: EMRI Image as an Enhanced MRI image
End – Algorithm

After image enhancement of the pre-processing step, we move towards the segmentation of the brain tumour as a foreground part of the MRI images. It contains the pixel of tumour region as well as extra pixel sets that are stored in the background of the segmented part. We present a comparative analysis of traditional segmentation as well as improved segmentation algorithms in this article for the segmentation of tumour Region of Interest (ROI) from brain MRI images. We focused on introducing a comparative ASBT system using six different scenarios such as:

ASBT System using FCM: This scenario of the proposed ASBT system is based on the FCM as a clustering-based segmentation approach that is an unsupervised process. The used FCM as a segmentation approach is a clustering method that allows one pixel of MRI image to belong to two or

more clusters and based on this architecture, FCM creates two parts of an MRI image that is known as background and foreground part where the foreground is the ROI of tumour.
The algorithm of FCM in proposed ASBT system is written as:

Algorithm 2: ASBT System using FCM

Input: Enhanced MRI Image →EMRI-Image
Output: Background and Foreground of MRI Image in terms of Tumour ROI →Background-Image and ROI-Images
Start segmentation
Initialize a group for segmentation (G = 2)
Calculate the size of EMRI-Image = [Row, Col.]
Initialize number of the cluster for segmentation, C = C1, and C2 // Where C1 for Background-Image and C2 for ROI-Image (Foreground Image)
Set clustering iterations, ITR = N
While ITR ≠N(if not reached max iteration)
For m = 1→ Row
For n = 1→Col
If M-Image (m, n)==C1
Background-Image (m, n) =EMRI-Image (m, n)
Else if EMRI-Image (m, n)==C2
ROI-Image (m, n) =EMRI-Image (m, n)
End – If
Adjust Centroid C using given equation 4

$$C_{mn} = (\sum_1^n [C1, C2] (\gamma_G^m * x_G) / \sum_1^n C1, C2] \gamma_G^m \quad (4)$$

Repeat until all pixel data not cover in the image and then calculate the distance (d) of data and define membership function given equation 5

$$[C1, C2] = \sum_1^n (d_{Gm}^2 / d_{Gn}^2)^{1/m-1}]^{-1} \quad (5)$$

End – For
End – For
End – While
Return: Background-Image and ROI-Imageas a segmented background and foreground of EMRI image
End – Algorithm

Using this algorithm, we segment the ROI of tumor from the MRI images and after the segmentation of MRI images using the FCM in the ASBT system, the obtained segmented result with original MRI images is shown in Fig. 4.

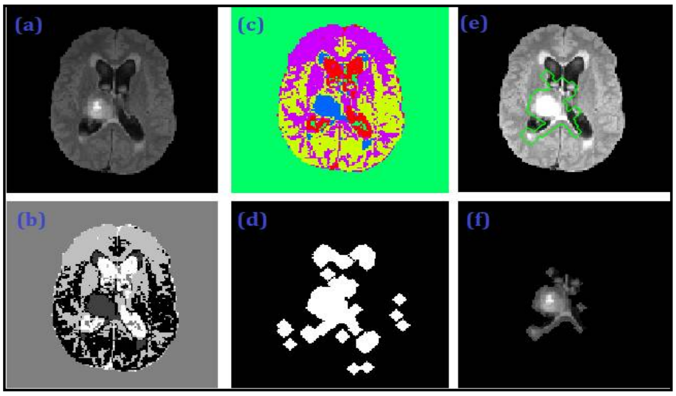


Fig.4: (a) MRI Image (b) Grey Labelled Image (c) Color Labelled Image (d) Mask Image of Tumour (e) Region of Tumour and (f) Segmented ROI using FCM

ASBT System using K-means*:* This is the second scenario of the proposed ASBT system and in this scenario, we used K-means as a segmentation technique instead of FCM because K-means helps to provide better segmentation results as compare to the FCM. By utilizing the concept of K-means, we can segment a more appropriate region of tumors from the MRI images but also the mix-up issues faced for low contrast images, and K-means cannot provide better segmentation results for all cases. This happens because it is a type of unsupervised clustering algorithm and can separate the input MRI image pixels into multiple clusters based on pixel intensity values and the algorithm of K-means for proposed ASBT system is written as:

Algorithm 3: ASBT System using K-means

Input: Enhanced MRI Image →EMRI-Image
Output: Background and Foreground of MRI Image in terms of Tumour ROI →Background-Image and ROI-Images
Start segmentation
Initialize a group for segmentation (G = 2)
Calculate the size of EMRI-Image = [Row, Col.]
Initialize number of the cluster for segmentation, C = C1, and C2 // Where C1 for Background-Image and C2 for ROI-Image (Foreground Image)
Set clustering iterations, ITR = N
While ITR ≠N (if not reached max iteration)
For m = 1 →Row
For n = 1 →Col
If EMRI-Image (m, n)==C1
Background-Image (m, n) =EMRI-Image (m, n)
Else if EMRI-Image (m, n)==C2
ROI-Image (m, n) =EMRI-Image (m, n)
End – If
Adjust Centroid C using their mean
C = Average (Background-Image, ROI-Image) using the given equation 6

$$C_{mn} = \sum_{m=1}^{Row}\sum_{n=1}^{Col}\frac{C1_{mn}+mn}{2} \qquad (6)$$

End – For
End – For
End – While
Return: Background-Image and ROI-Image as a segmented background and foreground of EMRI image
End – Algorithm

Based on the above written K-means algorithm in the ASBT system, we obtained better-segmented results as compare to the FCM-based ASBT system, and results with the original MRI image are shown in Fig. 5.

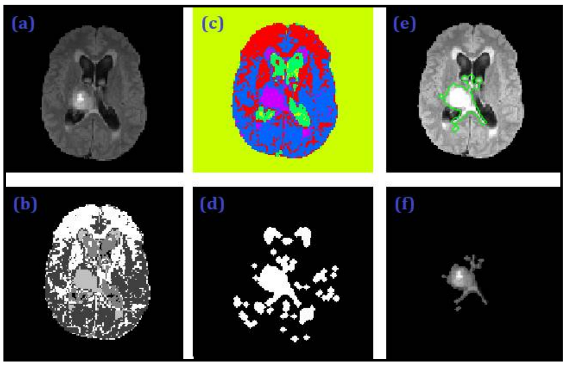


Fig.5: (a) MRI Image (b) Grey Labelled Image (c) Color Labelled Image (d) Mask Image of Tumour (e) Region of Tumour and (f) Segmented ROI using K-means

In the above Fig. 4 and 5, we used the concept of FCM or K-means for tumour region segmentation and the final segmented tumour is shown in the Fig. 4 or 5 (f) based on the centroid C1 and C2 for MRI image. An example for clustering approach for MRI image is shown in the Fig. 6

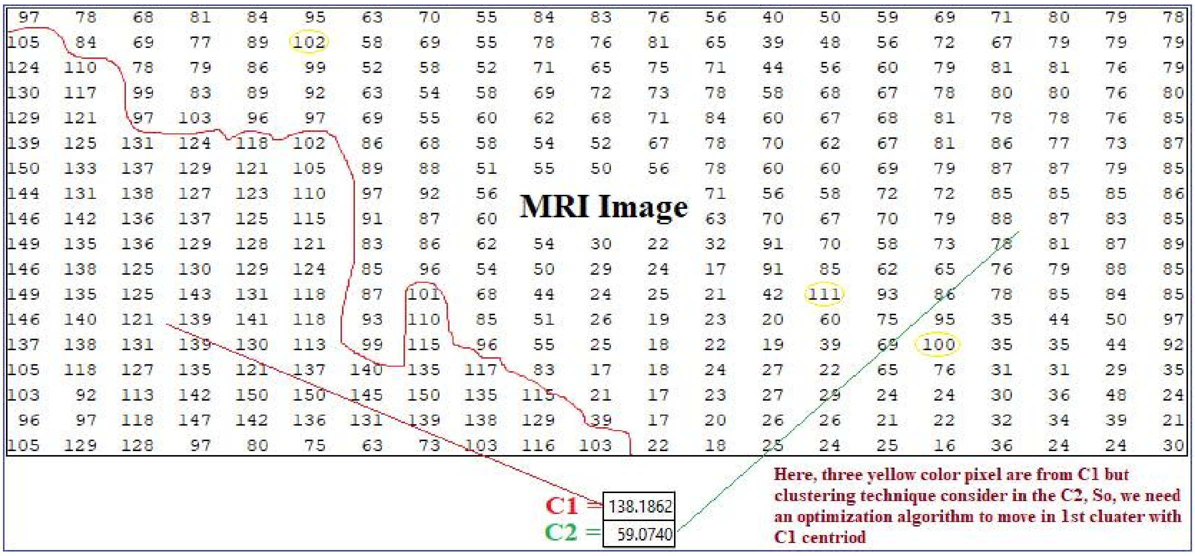


Fig.6: Example of MRI Tumor Segmentation

To minimize the above problem, we use the concept of swarm-based optimization technique with FCM and K-means in the below section.

ASBT System using FCM with PSO: The working of this scenario is similar to the FCM but in this, we used hybridization of FCM with PSO as a hybrid segmentation technique. PSO is the basic Metaheuristic swarm-based approach that is capable to solve the segmentation mix up a problem by utilizing the fitness function. PSO was established by Eberhart and Kennedy as an evolutionary image segmentation technique. The algorithm is bestowed with the ability to move over the search space and track their coordinates with fitness solutions to solve the problem of unsupervised FCM clustering to enhance the MRI image segmentation quality. The algorithm of FCM with PSO segmentation is written as:

Algorithm 4: ASBT System using FCM with PSO Technique

Input: Enhanced MRI Image →EMRI-Image

Output: Background and Foreground of MRI Image in terms of Tumour ROI →Background-Image and ROI-Images

Start segmentation

Initialize a group for segmentation (G = 2)

Calculate the size of EMRI-Image = [Row, Col. and D]

Initialize number of the cluster for segmentation, C = C1, and C2 // Where C1 for Background-Image and C2 for ROI-Image (Foreground Image)

Set clustering iterations, ITR = N

While ITR ≠N(if not reached max iteration)

For m = 1→ Row

For n = 1→Col

IfM-Image (m, n)==C1

Background-Image (m, n) =EMRI-Image (m, n)

Else if EMRI-Image (m, n)==C2

ROI-Image (m, n) =EMRI-Image (m, n)

End – If

AdjustCentroid C using given equation 4

Repeat until all pixel data not cover in the image and then calculate the distance (d) of data and define membership function given equation 5

End – For

End – For

End – While

To optimized the ROI-Image, PSO is used

Initialize PSO parameter – Iterations (T)

– Population Size (S) = Pixels presents in the EMRI-Image

– Lower Bound (LB) = 0

– Upper Bound (UB) = 256

– Fitness function

– Number of selection (N)

Calculate size in terms of T = Size (EMRI Image)
Define Fitness function:

$$\boldsymbol{fit(fun)} = \begin{cases} \mathbf{1} & \boldsymbol{ifpixelisless} \\ \mathbf{0} & \boldsymbol{otherwise} \end{cases} \quad \mathbf{(7)}$$

For l = 1 → T

$$fs = \mathrm{EMRI}(l)$$

$$ft = \frac{\sum_{i=1}^{Pixels} EMRI(l)}{LengthofEMRI\ Pixels}$$

$fit(fun)$ = fitness function which defines by above-given equation 7

$$Threshold_{value} = PSO\big(P, T, LB, UB, N, fit(fun)\big)$$

End – For
Set optimization iterations, OITR = N
While OITR ≠N(if not reached max iteration)

$$\boldsymbol{Threshold} = Threshold_{value}$$

Mask Image = Binary (ROI-Image, Threshold)
Boundaries = Find out boundary (Mask Image)
ROI Region = Boundaries
For k = 1→D
ROI-Image = EMRI-Image × ROI Region
End – For
Return: Background-Image and ROI-Image as a segmented background and foreground of EMRI image
End – Algorithm

Based on the above-written hybrid segmentation algorithm using FCM with PSO in ASBT system, we obtained better-segmented result as compare to the only FCM-based ASBT system and results with the original MRI image is shown in the Fig. 7.

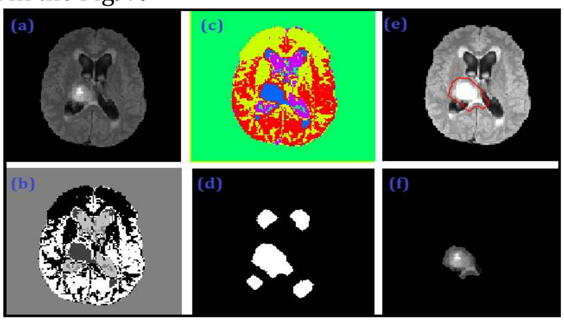


Fig.7: (a) MRI Image (b) Grey Labelled Image (c) Color Labelled Image (d) Mask Image of Tumour (e) Region of Tumour and (f) Segmented ROI using FCM with PSO

ASBT System using K-means with PSO: The working of this scenario is similar to the K-means but in this, we used hybridization of K-means with PSO as a hybrid segmentation technique. The algorithm of K-means with PSO segmentation is written as:

Algorithm 5: ASBT System using K-means with PSO Technique

Input: Enhanced MRI Image →EMRI-Image
Output: Background and Foreground of MRI Image in terms of Tumour ROI →Background-Image and ROI-Images
Start segmentation
Initialize a group for segmentation (G = 2)
Calculate the size of EMRI-Image = [Row, Col.]
Initialize number of the cluster for segmentation, C = C1, and C2 // Where C1 for Background-Image and C2 for ROI-Image (Foreground Image)
Set clustering iterations, ITR = N
While ITR ≠N(if not reached max iteration)
For m = 1 →Row
For n = 1 →Col
If EMRI-Image (m, n)==C1
Background-Image (m, n) =EMRI-Image (m, n)
Else if EMRI-Image (m, n)==C2
ROI-Image (m, n) =EMRI-Image (m, n)
End – If

Adjust Centroid C using their mean
C = Average (Background-Image, ROI-Image) using the given equation 6
End – For
End – For
End – While
To optimized the ROI-Image, PSO is used
Initialize PSO parameter – Iterations (T)
– Population Size (S) = Pixels presents in the EMRI-Image
– Lower Bound (LB) = 0
– Upper Bound (UB) = 256
– Fitness function
– Number of selection (N)
Calculate size in terms of T = Size (EMRI Image)
For l = 1 → T

$$fs = \mathrm{EMRI}(l)$$

$$ft = \frac{\sum_{i=1}^{Pixels} EMRI(l)}{Length of EMRI\ Pixels}$$

$fit(fun)$ = fitness function which defines by above-given equation 7

$$Threshold_{value} = PSO(P, T, LB, UB, N, fit(fun))$$

End – For
Set optimization iterations, OITR = N
While OITR ≠N(if not reached max iteration)

$$\boldsymbol{Threshold} = Threshold_{value}$$

Mask Image = Binary (ROI-Image, Threshold)
Boundaries = Find out boundary (Mask Image)
ROI Region = Boundaries
For k = 1→D
ROI-Image = EMRI-Image × ROI Region
End – For
Return: Background-Image and ROI-Image as a segmented background and foreground of EMRI image
End – Algorithm

Based on the above-written hybrid segmentation algorithm using K-means with PSO in ASBT system, we obtained better-segmented result as compare to the only K-means-based ASBT system and results with the original MRI image is shown in the Fig. 8.

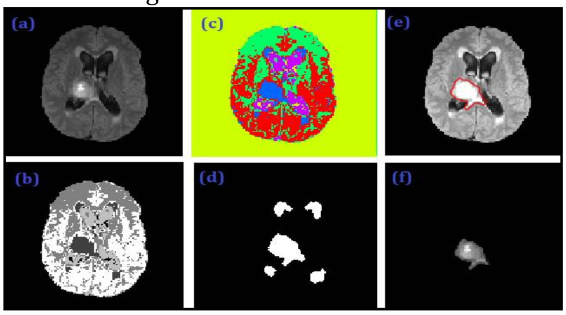


Fig.8: (a) MRI Image (b) Grey Labelled Image (c) Color Labelled Image (d) Mask Image of Tumour (e) Region of Tumour and (f) Segmented ROI using K-means with PSO

ASBT System using FCM with GOA: In this scenario, we used FCM with GOA as an optimization algorithm instead of PSO to design a hybrid segmentation technique because we present a comparative analysis of segmentation approaches for brain tumor segmentation. Here, the separation or pixel mix up the problem of FCM is solved by using the GOA with the help of an optimal and novel fitness function. GOA is a swarm-based bio-inspired metaheuristic algorithm that is inspired by the behavior of grasshopper (Insects) to help to search the pixels mix-up problem during the segmentation and then separate them by utilizing the concept of morphological operations. The algorithm of FCM with GOA as a hybrid segmentation in ASBT system is written as:

Algorithm 6: ASBT System using FCM with GOA Technique

Input: Enhanced MRI Image →EMRI-Image

Output: Background and Foreground of MRI Image in terms of Tumour ROI →Background-Image and ROI-Images
Start segmentation
Initialize a group for segmentation (G = 2)
Calculate the size of EMRI-Image = [Row, Col. and D]
Initialize number of the cluster for segmentation, C = C1, and C2 // Where C1 for Background-Image and C2 for ROI-Image (Foreground Image)
Set clustering iterations, ITR = N
While ITR ≠N(if not reached max iteration)
For m = 1→ Row
For n = 1→Col
IfM-Image (m, n)==C1
Background-Image (m, n) =EMRI-Image (m, n)
Else if EMRI-Image (m, n)==C2
ROI-Image (m, n) =EMRI-Image (m, n)
End – If
AdjustCentroid C using given equation 4
Repeat until all pixel data not cover in the image and then calculate the distance (d) of data and define membership function given equation 5
End – For
End – For
End – While
To optimized the ROI-Image, GOA is used
Set up basic parameters of GOA: Population of Grasshopper (P_G) – Pixel count in EMRI Image
Define the position function:

$$\boldsymbol{v(r) = v_0 \times exp(-distance^m), \quad if\ m \geq 1}$$

Wheredistance= distance between any two grasshopper
$\boldsymbol{v}_0$ = initial velocity at d=0
m = Position of Grasshoppers (P_G)
Define novel Fitness Function:

$$\boldsymbol{fun(fit) = \begin{cases} 1; & if\ EMRI - Image_{Pixel} < Threshold_{Pixel} \\ 0; & Otherwise \end{cases}} \quad \textbf{(8)}$$

Set,ROI-Image and Background-Images = []
For m = 1→Row
For n = 1→Col
C_G = M-Image (m, n)
$M_G = \sum_1^m \sum_1^n \frac{EMRI-Image(m,n)}{m \times n}$
Threshold = GOA (fun (fit), C_G,M_G)
End – For
End – For
If EMRI-Image (Pixels) > Threshold
ROI-Image = EMRI-Image
Else
Background-Image = EMRI-Image
End – If
Set optimization iterations, OITR = N
While OITR ≠N(if not reached max iteration)
Mask Image = Binary (ROI-Image, Threshold)
Boundaries = Find out boundary (Mask Image)
ROI Region = Boundaries
For k = 1→D
ROI-Image = EMRI-Image × ROI Region
End – For
Return: Background-Image and ROI-Image as a segmented background and foreground of EMRI image
End – Algorithm

With the help of the above-mentioned hybrid segmentation algorithm using FCM with GOA, the segmented results are shown in Fig. 9.

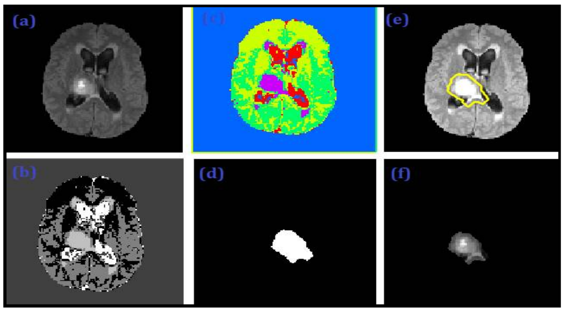


Fig.9: (a) MRI Image (b) Grey Labelled Image (c) Color Labelled Image (d) Mask Image of Tumour (e) Region of Tumour and (f) Segmented ROI using FCM with GOA

ASBT System using K-means with GOA: This is the last scene of the proposed comparative ASBT system and we used K-means with GOA as a hybrid segmentation technique with a novel fitness function defined in equation 8. The algorithm of K-means with GOA as a hybrid segmentation in ASBT system is written as:

Algorithm 7: ASBT System using K-means with GOA Technique

Input: Enhanced MRI Image →EMRI-Image
Output: Background and Foreground of MRI Image in terms of Tumour ROI →Background-Image and ROI-Images
Start segmentation
Initialize a group for segmentation (G = 2)
Calculate the size of EMRI-Image = [Row, Col. and D]
Initialize number of the cluster for segmentation, C = C1, and C2 // Where C1 for Background-Image and C2 for ROI-Image (Foreground Image)
Set clustering iterations, ITR = N
While ITR ≠N(if not reached max iteration)
For m = 1→ Row
For n = 1→Col
If M-Image (m, n)==C1
Background-Image (m, n) =EMRI-Image (m, n)
Else if EMRI-Image (m, n)==C2
ROI-Image (m, n) =EMRI-Image (m, n)
End – If
Adjust Centroid C using given equation 6
C = Average (Background-Image, ROI-Image) using the given equation 6
End – For
End – For
End – While
To optimized the ROI-Image, GOA is used
Set up basic parameters of GOA: Population of Grasshopper (P_G) – Pixel count in EMRI Image
Define the position function:

$$\boldsymbol{v(r) = v_0 \times exp(-distance^m), \quad if\ m \geq 1}$$

Where, distance= distance between any two grasshopper
v_0 = initial velocity at d=0
m = Position of Grasshoppers (P_G)
Set, ROI-Image and Background-Images = []
For m = 1→Row
For n = 1→Col
C_G = M-Image (m, n)
$M_G = \sum_1^m \sum_1^n \frac{EMRI-Image(m,n)}{m \times n}$
Threshold = GOA (fun (fit), C_G,M_G)
End – For
End – For
If EMRI-Image (Pixels) > Threshold
ROI-Image = EMRI-Image
Else
Background-Image = EMRI-Image
End – If

Set optimization iterations, OITR = N
While OITR ≠N(if not reached max iteration)
Mask Image = Binary (ROI-Image, Threshold)
Boundaries = Find out boundary (Mask Image)
ROI Region = Boundaries
For k = 1→D
ROI-Image = EMRI-Image × ROI Region
End – For
Return: Background-Image and ROI-Image as a segmented background and foreground of EMRI image
End – Algorithm

With the help of above-mentioned proposed hybrid algorithm using the K-means along with the GOA as an optimization technique, we segment the tumor region from MRI images with maximum accuracy as compare to others scenarios and the segmented result with original images is shown in the Fig. 10.

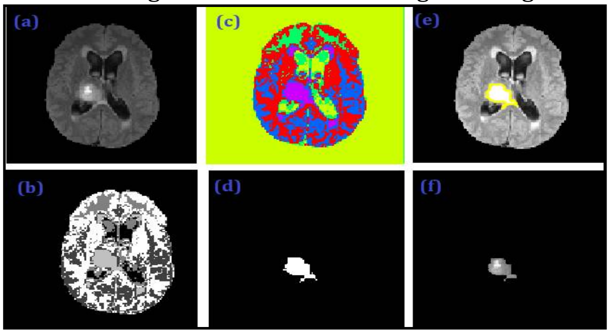


Fig.10: (a) MRI Image (b) Grey Labelled Image (c) Color Labelled Image (d) Mask Image of Tumour (e) Region of Tumour and (f) Segmented ROI using K-means with GOA

At last of simulation, the performance parameters of the proposed comparative ASBT system are calculated and compare all six scenarios that are explained in the above section of the research article in terms of Accuracy, Sensitivity, F-measure, Precision, MCC, Dice, Jaccard, Specificity and Time Complexity. By using the above hybrid segmentation procedure, we achieve better experimental and brain tumor segmentation results that are well described in the next section of this research paper on behalf of some sample MRI images. The list of used sample MRI images from the BraTS Dataset is shown in Fig. 11.

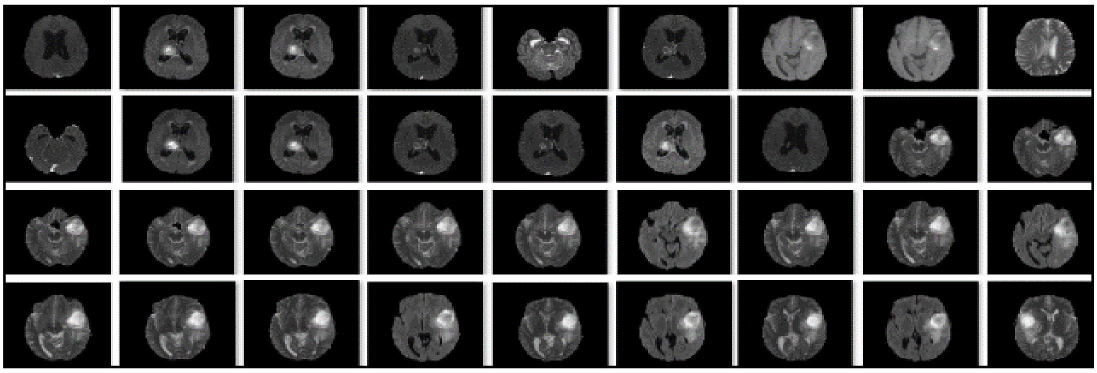
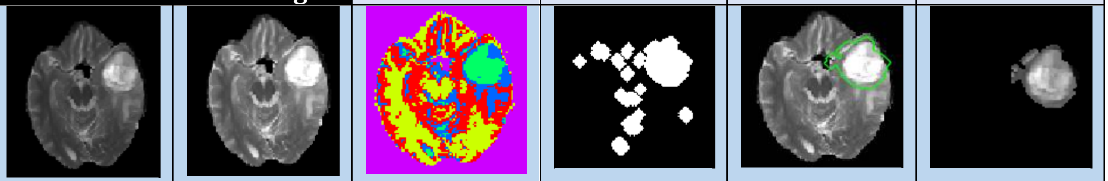
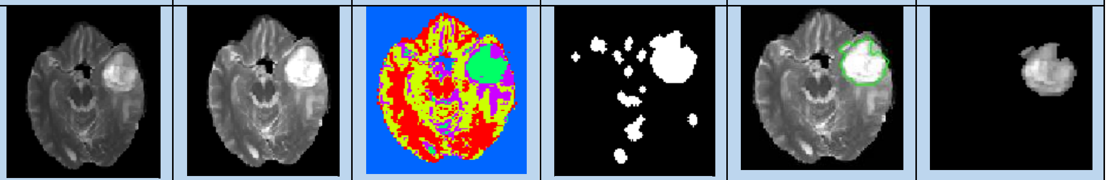
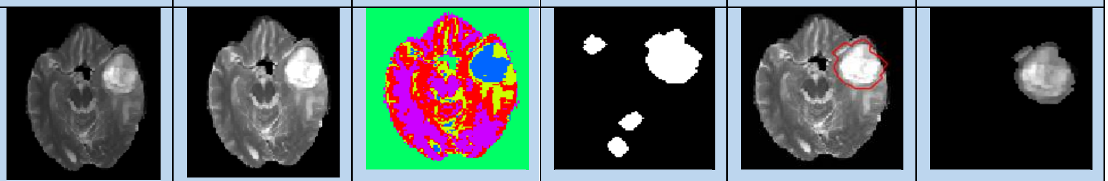
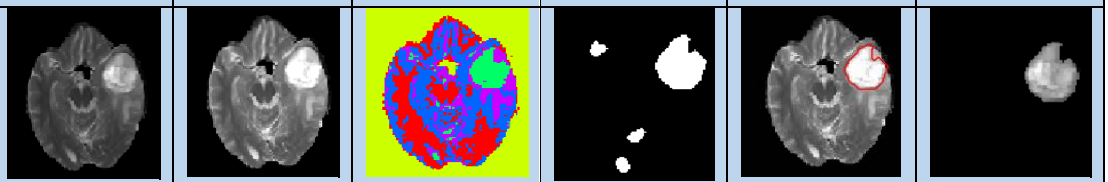
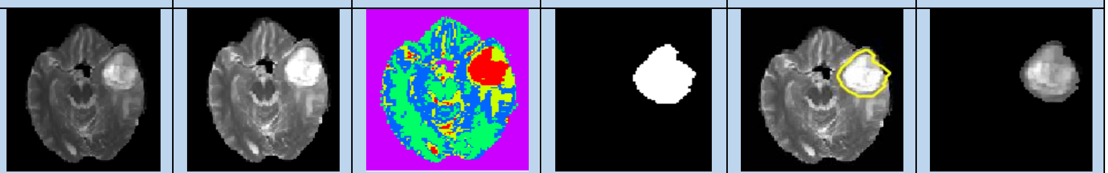
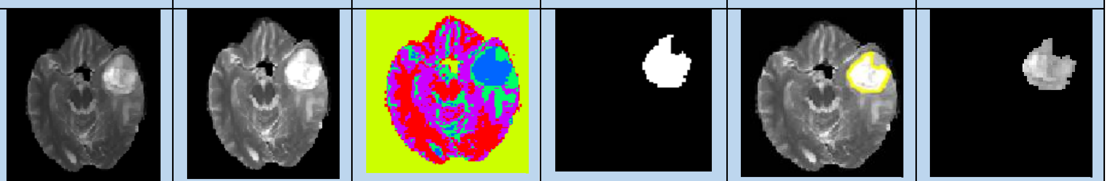


Fig.11: Brain MRI Images form BraTS Dataset

The sample image is taken for the simulation of the proposed ASBT system from the BraTS standard dataset and it contains multimodal MRI scan images that provide comprehensive data. For the simulation of the model, DICOM files are converted into PNG format that is representing multi-frame covered brain images that were extracted from the dataset are analyzed to evaluate the proposed comparative ASBT system. The used BraTS dataset is accessible at the given link: http://braintumorsegmentation.org/

The goal of this research work is to provide a comparative analysis for research on image edge and gradient detection and we try to achieve better results in this area that helps to analyze an image properly. The simulation results of the proposed comparative model are described in Table I with the original images.

Table 1: Brain Tumour Segmentation Comparison

Method	Original MRI Images	Pre-processed MRI Images	Segmented Images			
			Labeled	*Mask*	*Region*	*Tumour*
FCM						
K-means						
FCM with PSO						
K-means with PSO						
FCM with GOA						
K-means with GOA						

Based on the above-mentioned dataset of a sample image that is used for the testing of the proposed comparative model of the image edge detection using the hybridization of fuzzy logic with the gradient as well standard deviation mechanism. The simulation outcomes of the proposed model are shown in the next section of the research article.

RESULTS AND DISCUSSION

In this research work, we proposed a comparative ASBT system for the brain tumour segmentation from MRI images using the six different scenarios such as FCM, K-means, FCM with PSO, K-means with PSO, FCM with GOA and K-means with GOA. The experimental results of the brain tumour segmentation from MRI images for the five sample test images are described in this section and comparing with existing work. It is detected that the segmented brain tumor ROI obtained as a result of the combination of K-means with GOA is much better for all the test MRI images to compare to other techniques. The brain tumour ROI in the segmented images in column 5 of Table I is more precisely marked concluding it to be the best among the six segmentation techniques of brain tumour.

In this section, we relate the segmentation results of the six different segmentation scenarios in Table II to X based on the Accuracy, Sensitivity, F-measure, Precision, MCC, Dice, Jaccard, Specificity and Time Complexity.

Table 2: Accuracy (%) Comparison of Proposed ASBT System

S. No.	FCM	K-means	FCM with PSO	K-means with PSO	FCM with GOA	K-means with GOA
1	90.77	94.01	95.39	96.96	98.43	99.87
2	91.22	94.86	94.95	96.46	98.08	99.56
3	90.05	92.66	95.14	96.71	97.43	99.58
4	90.32	93.11	95.08	95.86	97.33	99.73
5	91.41	92.32	95.50	96.63	96.78	99.28

Table 3: Sensitivity Comparison of Proposed ASBT System

S. No.	FCM	K-means	FCM with PSO	K-means with PSO	FCM with GOA	K-means with GOA
1	0.9614	0.9622	0.9703	0.9727	0.9852	0.9937
2	0.9616	0.9702	0.9761	0.9843	0.9724	0.9926
3	0.9608	0.9688	0.9707	0.9654	0.9871	0.9965
4	0.9685	0.9760	0.9856	0.9862	0.9899	0.9942
5	0.9649	0.9653	0.9658	0.9673	0.9676	0.9815

Table 4: F-measure Comparison of Proposed ASBT System

S. No.	FCM	K-means	FCM with PSO	K-means with PSO	FCM with GOA	K-means with GOA
1	0.1927	0.3052	0.5998	0.7082	0.8093	0.8345
2	0.2162	0.5915	0.6353	0.6572	0.8433	0.8655
3	0.2314	0.3151	0.5713	0.6102	0.6383	0.7447
4	0.3486	0.3923	0.4982	0.6708	0.7852	0.7927
5	0.4347	0.7822	0.8779	0.9331	0.9564	0.7369

Table 5: Precision Comparison of Proposed ASBT System

S. No.	FCM	K-means	FCM with PSO	K-means with PSO	FCM with GOA	K-means with GOA
1	0.1071	0.1814	0.4341	0.5569	0.6867	0.7194
2	0.1218	0.4255	0.4709	0.4933	0.7446	0.7674
3	0.1316	0.1882	0.4048	0.4461	0.4717	0.5945
4	0.2126	0.2455	0.3334	0.5083	0.6507	0.6582
5	0.2806	0.6573	0.8047	0.9013	0.9455	0.5899

Table 6: MCC (Matthews Correlation Coefficient) Comparison of Proposed ASBT System

S. No.	FCM	K-means	FCM with PSO	K-means with PSO	FCM with GOA	K-means with GOA
1	0.4526	0.4557	0.4692	0.5639	0.6052	0.8273
2	0.3962	0.5133	0.8292	0.9085	0.9529	0.9969
3	0.3061	0.3434	0.5178	0.5272	0.6472	0.9181
4	0.5564	0.6935	0.7396	0.7804	0.848	0.8489
5	0.5398	0.5504	0.5634	0.6121	0.6586	0.9393

Table 7: Dice Coefficient Comparison of Proposed ASBT System

S. No.	FCM	K-means	FCM with PSO	K-means with PSO	FCM with GOA	K-means with GOA
1	0.261	0.4461	0.5435	0.6784	0.7783	0.781
2	0.3458	0.5126	0.513	0.5631	0.6655	0.9714
3	0.3106	0.4694	0.4896	0.6785	0.7177	0.7809
4	0.7382	0.7944	0.8202	0.8559	0.8897	0.9194
5	0.3392	0.4129	0.5522	0.5543	0.9745	0.9962

Table 8: Jaccard Comparison of Proposed ASBT System

S. No.	FCM	K-means	FCM with PSO	K-means with PSO	FCM with GOA	K-means with GOA
1	0.2137	0.5091	0.6243	0.8404	0.8455	0.8968
2	0.4874	0.5388	0.7795	0.8184	0.8516	0.9099
3	0.2123	0.3325	0.4977	0.6438	0.6984	0.7602
4	0.2323	0.3467	0.8579	0.8665	0.8802	0.9166
5	0.1016	0.1993	0.3016	0.3529	0.8555	0.9099

Table 9: Specificity Comparison of Proposed ASBT System

S. No.	FCM	K-means	FCM with PSO	K-means with PSO	FCM with GOA	K-means with GOA
1	0.9116	0.9291	0.9324	0.9555	0.9682	0.9736
2	0.9121	0.9222	0.9433	0.9715	0.9779	0.9968
3	0.9261	0.9356	0.9389	0.9774	0.9803	0.9998
4	0.937	0.9399	0.9449	0.9549	0.9838	0.9907
5	0.9139	0.9337	0.9438	0.9515	0.9615	0.9765

Table 10: Time Complexity (s)Comparison of Proposed ASBT System

S. No.	FCM	K-means	FCM with PSO	K-means with PSO	FCM with GOA	K-means with GOA
1	1.257	3.129	4.705	2.733	1.275	0.879
2	1.875	2.502	3.007	2.717	1.822	0.848
3	1.032	2.241	2.407	2.712	2.674	0.934
4	2.484	2.833	2.837	1.166	2.688	0.744
5	1.497	2.991	4.656	3.864	1.955	1.103

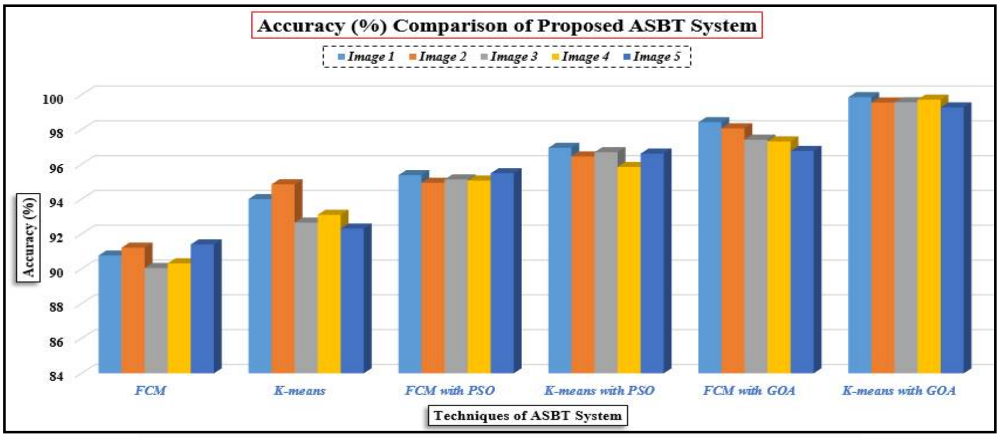


Fig 12: Accuracy (%) Comparison of Proposed ASBT System

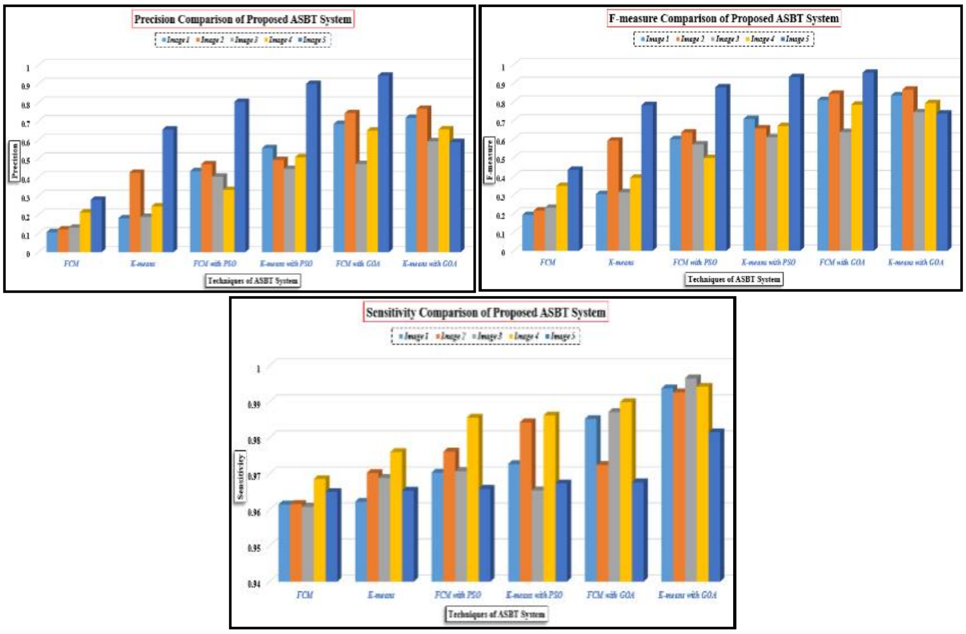


Fig 13: Comparison of Sensitivity, Precision and F-measure of Proposed ASBT System

The performance parameters are calculated to validate the proposed comparative ASBT system by evaluate the performance of segmentation approach and the formula of some basic parameters that is used in our proposed system are described as:

$$Precision = \frac{True_{Positive}}{True_{Positive}+False_{Positive}} \quad (9)$$

$$Sensitivity = \frac{True_{Positive}}{True_{Positive}+False_{Negative}} \quad (10)$$

$$F - measure = 2 * \frac{Precision*Recall}{Precision+Recall} \quad (11)$$

$$Accuracy = \frac{True_{Positive} + True_{Negative}}{True_{Positive} + True_{Negative} + False_{Positive} + False_{Negative}} \quad (12)$$

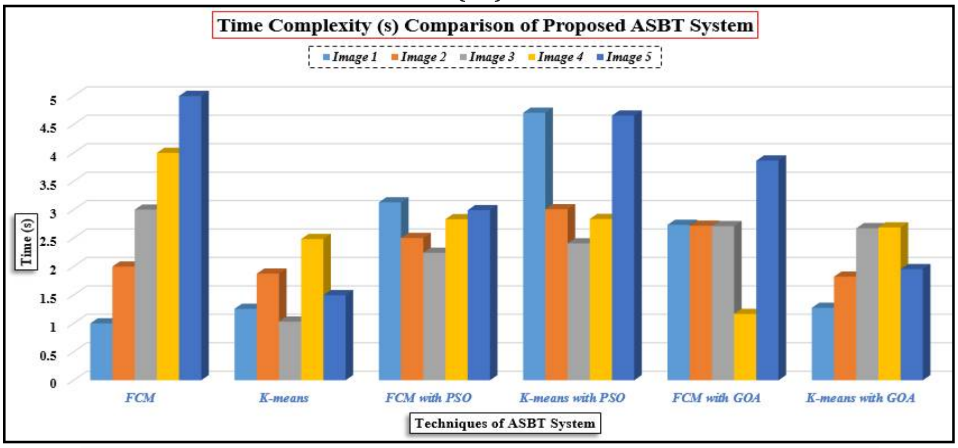


Fig 14: Comparison of Time Complexity of Proposed ASBT System

Table 11: Comparison with Existing Work

Authors/Techniques	Accuracy (%)
MS Alam et al. [12]	97.50
A Bousselham et al. [13]	97.74
FCM	90.75
K-means	93.39
FCM with PSO	95.21
K-means with PSO	96.52
FCM with GOA	97.61
K-means with GOA	99.61

The comparison of proposed ASBT system with some other existing work based on the brain tumour segmentation using MRI images, which is considered in survey of this research article, is described in below Table XI and according to the observed values, we draw a comparison graph of proposed model with existing works based on the different approaches and algorithm for segmentation as well as training and classification purpose in the developed model.

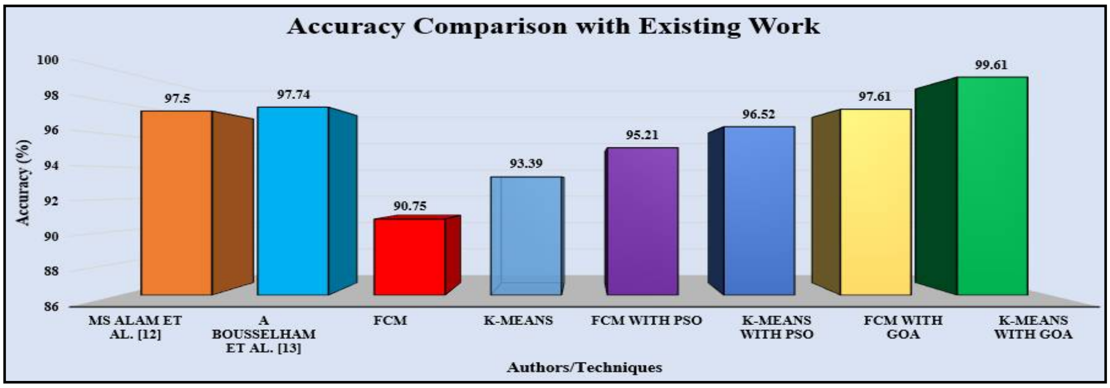


Fig. 15: ASBT System Accuracy Comparison with Existing Work

The comparison of the proposed ASBT system with six different approaches is compared with the existing work in Fig.15. From the figure, we observe that the accuracy achieved by the proposed ASBT system using the concept of hybridization of K-means with GOA is better than other techniques or other authors' work for segmentation of tumour region from the MRI image. By using the hybrid segmentation approach of K-means with GOA as an optimization technique achieve more than 99% segmentation accuracy and we can say the effectiveness of the proposed ASBT system with K-means and GOA more compare to others.

From the experimental analysis, we conclude that the combination of K-means with GOA is better option to design a brain tumor classification model in future using the concept of image processing approaches for early-stage detection of benign types of tumor to save the human lives. Because the classification accuracy of brain tumor classification model is directly proportional to the segmentation accuracy, so above results depicts the hybridization of the K-means with GOA for tumor region segmentation would be help better classification accuracy. But the proposed ASBT system is limited for only BraTS dataset for and in case of other dataset accuracy may be vary and segmentation time will be minimized by utilizing the standard size of image.

CONCLUSION

In this paper, we have introduced a comparative ASBT system for the brain tumour segmentation from the MRI images using the concept of improvisation of the traditional clustering mechanism. We proposed an ASBT system using the six different scenarios such as FCM, K-means, FCM with PSO, K-means with PSO, FCM with GOA, and K-means with GOA. We have used to the publicly available BraTS Dataset that contains MRI images of the human brain in the form of DICOM but we covert the format into JPG for the test sample. All developed brain tumour segmentation algorithms are compared with each other based on accuracy, sensitivity, F-measure, precision, mcc, dice, Jaccard, specificity, and time complexity and also compare the best out of these models with different state-of-the-art. The proposed model segmentation accuracy is reported when the proposed model is simulated on MRI image from the BraTS dataset is more than 99% whereas the existing work non-hybrid model accuracy is comparatively less. In future, the proposed ASBT system can be extended for large MRI images dataset that contains more than one million MRI images as well as low contrast image because of the system accuracy decrease for low contrast MRI image.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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CITATION OF THIS ARTICLE

N Bhagat, G Kaur. Automatic segmentation of Brain tumour using improved clustering mechanism. Bull. Env.Pharmacol. Life Sci., Spl Issue [1] 2022 : 440-458