Analysis And Evaluation Of Brain Tumour Detection From MRI Using F-PSO And FB-K Means

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***Abstract*—This Magnetic Resonance Imaging (MRI) has become an effective tool for clinical diagnoses and research in recent years. The technique for tumor detection employed Fuzzy Bisector based K-means clustering (FB-K means) technique for segmentation, FFT, curve analysis and K-space for feature extraction and finally, Fractional PSO (F-PSO) based Neural Network for classification. Later on the technique is planned and implemented, its efficiency and prosperity need to be tested. Hence, in this paper, the technique is analyzed and valued in a more elaborate and in-depth manner. More simulation results including that of skull stripping, histogram equalization, segmentation and classification are added for more understanding. Segmentation efficiency is added in a detailed way, evoking the true positive rate and segmentation rate. Thorough experimental analysis is held out by detecting out the evaluation parameters including true positive, false positive, false positive, false negative, sensitivity, specificity and accuracy varying cluster sizes. Average sensitivity, specificity and accuracy values came about 0.77, 0.80 and 0.78 respectively for the technique. Robustness analysis is borne out to find out noise suppression ability under various sorts of disturbances such as salt and pepper, Gaussian, speckle and Poisson. Comparative analysis is also carried out by comparing to conventional techniques. Computational analysis is also performed for finding efficiency based on time of computation and other training details. The analysis and evaluation infers that the technique performed well by obtaining good evaluation parameters. The technique also achieved good robustness and efficiency**

Keywords- MRI Image Segmentation, Tumour Detection, Analysis, Evaluation, Fuzzy Bisector K-means clustering, Classification, Fractional PSO based Neural Network.

I. INTRODUCTION

Medical images build essential portions for making out and investigating dissimilar body structures and the diseases offensive them [8, 9]. Magnetic resonance imagery (MRI) has been widely researched and is utilized for early detection of irregularities in brain parts [19]. It has become a very useful medical modality for the detection of brain tumor as it produces no tissue damage with its radiation and provides high tissue information. Brain tumor is an aggregation of abnormal cells that brings up within the head or around the brain [16, 17]. Brain image segmentation of MRI images is complicated and challenging, but its precise and exact segmentation is necessary for tumor detection and their classification [10, 11]. Image segmentation is first and very important step in image analysis. The primary idea of image segmentation is to simplify and change the picture into an easier and meaningful pattern to study. The mission of image segmentation is to separate an image into non-intersecting regions based on intensity or textural information [13]. Image segmentation is processed, which locate objects in an image [12]. Many segmentation algorithms have been created in different applications. The image segmentation is a crucial factor for the image processing. It becomes especially difficult in the cases of medical images, because of variations and diverse situations. In the majority of biomedical applications, the final segmentation goal is to produce the rules for classification of the regions obtained. Therefore, the image features must be analyzed carefully [15]. The segmentation of images can also be performed with the use of segmentation algorithms as well as clustering algorithms. Prominent clustering algorithms include K-means and FCM and finds applications in vast areas [14]. For classification many classifiers such as neural networks, SVM and fuzzy classifier are commonly employed [18].

After segmentation algorithm is designed and implemented, its efficiency and prosperity need to be tested. Segmentation efficiency is commonly broken down using the true positive rate and the segmentation rate for the input image. Evaluation matrices form an important parameter in deciding the robustness of the proficiency. Normally used evaluation parameters for disease diagnosis are false positive, false positive, false negative sensitivity, specificity and accuracy. Robustness analysis also yields a deep insight into how the technique is executed in case of disturbances. Salt and pepper, Gaussian, speckle and Poisson are examples of noises [19]. Thither are a handful of researches for segmentation of MRI images for tumor detection in the literature and some of the techniques talked about below. Samir Kumar Bandhyopadhyay and Tuhin Utsab Paul [1] proposed a system of image registration and data fusion theory adapted for the segmentation of MR images. This arrangement offered an effective and fast way for diagnosis of the brain tumor. They used multiple forms and improved K -means algorithm with dual localization methodology. Chunming Li et al. [2] Presented region-based method for image segmentation, which was able to deal with intensity inhomogeneities in the division. A. K. Qin and David A. Clausi [3] presented Markov random field (MRF) based multivariate segmentation algorithm called "multivariate iterative region growing using semantics" (MIRGS). In MIRGS, the impact of intercourse variation and computational cost were reduced using the MRF spatial context model incorporated with adaptive edge penalty and applied to neighborhoods.

Shandong Wu et al. [5] Proposed a method for brain tumor segmentation in MRI by adapting the sparse optimization techniques. The essence of the method lies in the subspace decomposition of the tissue feature space constituted by the brain MR images. They decomposed into two components: the low-rank normal brain tissue structures and the sparse corruption/error that was due to the developed tumor. Mohamed Ben Salah et al. [6] Investigated multi-region graph cut image partitioning via kernel mapping of the image data. The image data were transformed implicitly by a kernel function so that the piecewise constant model of the graph cut formulation became applicable. B. Venkateswara Reddy et al. [7] Proposed an intelligent segmentation technique to distinguish normal and abnormal slices of brain MRI data. It consisted of four steps which includes preprocessing, segmentation using Modified fuzzy C-means algorithm, feature extraction and final classification using the support vector machine.

The remainder of the paper is formed as follows: Section 3 gives system model, section 3 gives performance analysis and section 4 passes on the conclusion.

II. System Model

The technique for brain tumor detection employing fuzzy bisector K-means and fractional PSO based neural network is briefed in this section. The technique employs four modules, namely initial processing module, segmentation module, feature extraction module and classification module. The system model block diagram is presented in figure 1.

A. *Initial Processing Module*

The initial processing section consists of RGB to gray conversion, skull strip removal and histogram equalization. In conversion to grayscale, the input image (in RGB format) is converted to a grayscale image. Skull stripping refers to the removal of the scalp, skull and dura (non-brain structures) from the brain image to deliver the required image for tumor detection. The method uses intensity thresholding followed by removal of narrow connections to get a required brain image for tumor detection. After intensity thresholding, morphological operations are used for removal of narrow links. Histogram equalization is applied, hence as to improve the contrast of the icon which will improve the feature extraction procedure.

B. *Segmentation Module*

Fuzzy Bisector K-Means clustering (FB-KC) is utilized as the segmentation technique. In FB-KC, fuzzy bisector is combined with normal K-means algorithm to deliver enhanced and more accurate outcomes. The fuzzy bisection operation is performed with the help of defined fuzzy rules having certain parameters. The parameters involved are Minimum Squared Error (MSE) and number of pixels in the cluster. Based on these parameters, a certain cluster is selected and is divided into two with the help of the K - means algorithm. Final segments are made later on a specified number of phases and in every phase; one bisection operation is carried out where the selected cluster is split into two clumps. That is, in every phase, the number of clusters increases by one.

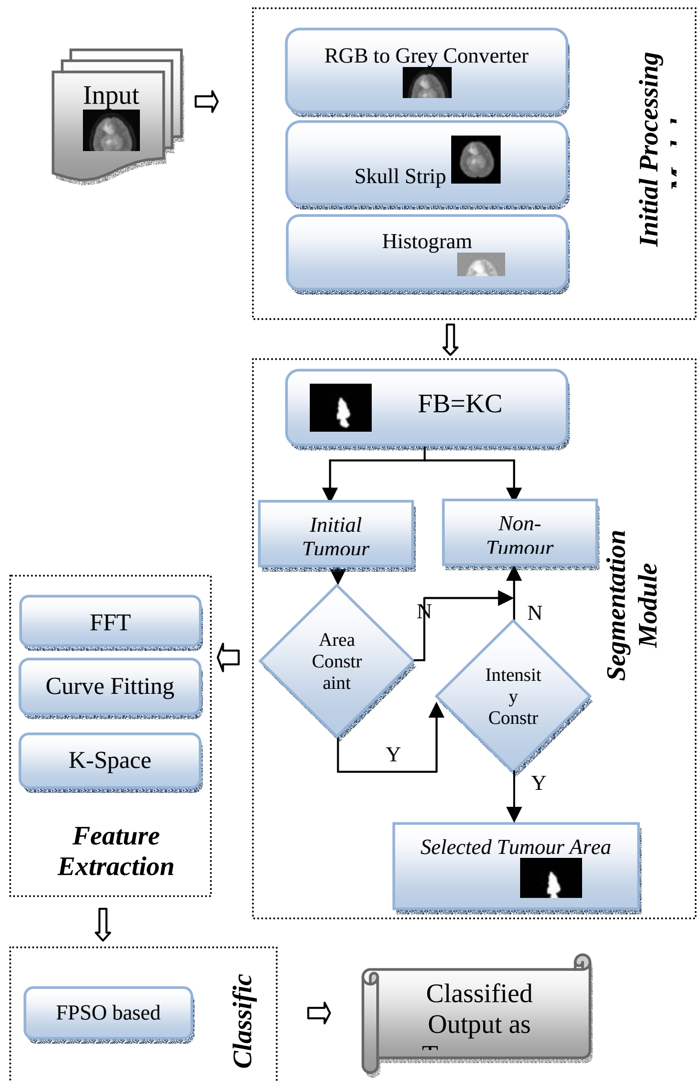


Fig 1: System model of the brain tumour detection

Identify applicable sponsor/s here. *(sponsors)*

III. FEATURE EXTRACTION AND CLASSIFICATION MODULE

Features are drawn out from the segmented portions with the use of 3 different attacks, namely FFT, curve fitting and K-space. Five characteristics are extracted in total from the segments, including entropy and coordinate values. Features include entropy feature is excerpted from the FFT transformed image, the control point coordinates values are chosen as the feature spots from the image using curve fitting and two features from k-space.

The classification is carried out with the help of Fractional PSO based Neural Network. For a classification task, ANNs needs to be “trained” for the network to be able to get the desired input-output map [20]. In the training phase, a set of example data is exhibited to the network and the connection weights of the network are adjusted by using PSO based back propagation algorithm. In PSO, each member of the population is called a particle and the population is called a swarm. Commencing with a randomly initialized population and moving in randomly chosen directions, each particle goes through the searching space and remembers the best previous positions and velocity of itself and its neighbors. The positions and velocity are updated at every step and compared with the fitness function defined. The use of the weight adjustment is to enable the net to “learn” so that the network would adapt to the given training data.

IV. PERFORMANCE ANALYSIS AND EVALUATION

The detailed analysis of the technique is carried out in this section. 3.1 briefs experimental environments, 3.2 describes evaluation parameters, 3.3 displays simulation results, 3.4 gives the segmentation results, 3.5 gives performance analysis, 3.6 gives a robustness analysis and 3.7 gives a computational analysis.

A. Experimental Environment

The technique is implemented using MATLAB on a system having the configuration of:

- 6 GB RAM
- 2.8 GHz
- Intel i-7 processor

The MRI image dataset employed are chosen from the publicly available sources. Sample images consist of tumor images and normal images.

B. Evaluation Parameters

The evaluation parameters used for evaluation are sensitivity, specificity and accuracy [21]. True positive (TP), True negative (TN), False negative (FN) and False positive (FP) are found out prior to finding the above parameters. TP, TN, FN and FP are defined in table 3.

Experimental Outcome	*Condition as determined by the Standard of Truth*	*Definition*
Positive	Positive	True Positive (TP)
Positive	Negative	False Positive (FP)
Negative	Positive	False Negative (FN)
Negative	Negative	True Negative (TN)

Table 3: Table defining TP, FP, FN and TN

The evaluation metrics of sensitivity, specificity and accuracy can be stated in the terms of TP, FP, FN and TN. Sensibility is the ratio of true positives that are correctly identified by a diagnostic trial. It indicates how well the test is at detecting a disease.

$$\mathrm{Sensitivity} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FN})$$

Specificity is the ratio of the true negatives correctly identified by a diagnostic trial. It indicates how good the test is at identifying normal (negative) condition.

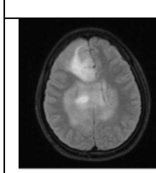
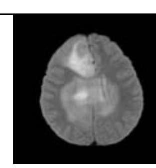
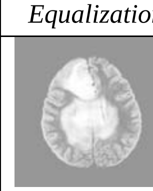
$$Specificity = TN/(TN + FP)$$

Accuracy is the ratio of true results, either true positive or true negative, in a population. It evaluates the degree of veracity of a diagnostic exam on a shape.

$$Accuracy = (TN + TP)/(TN + TP + FN + FP)$$

C. Simulation Results

In this segment, the simulation results are applied. In table 4, the simulation results obtained for the initial processing are presented where the input image, the image obtained after skull stripping and after histogram equalization is displayed. In table 5, the input image, segmented image and the classified output are fed.

Input Image	*After Skull stripping*	*After Histogram Equalization*
		

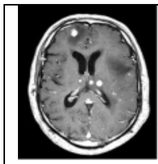
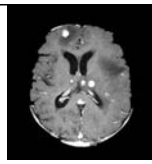
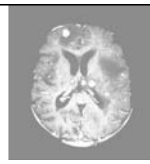
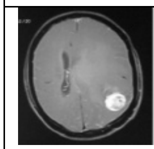
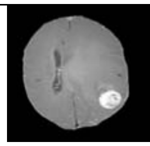
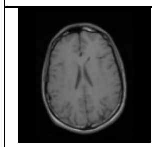
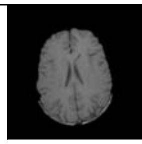
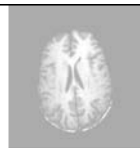
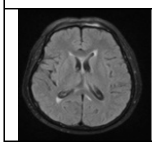
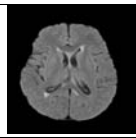
		
		
		
		

Table 4: Simulation results for initial processing

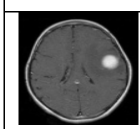
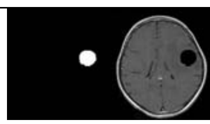
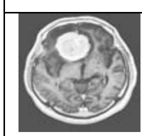
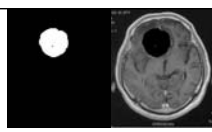
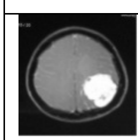
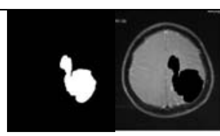
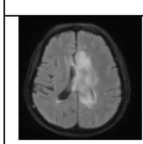
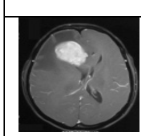
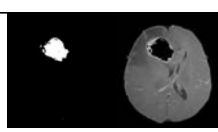
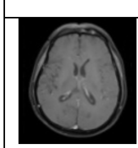
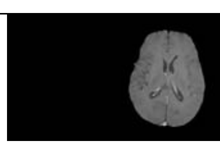
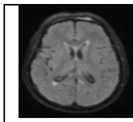
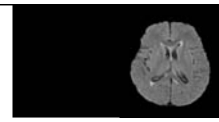
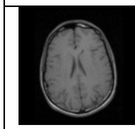
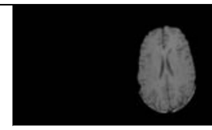
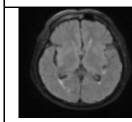
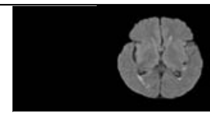
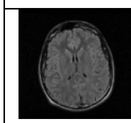
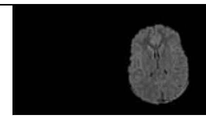
Input Image	*Segmented Image*	*Classified Output*
		Tumour
		Tumour
		Tumour
		Tumour
		Non-Tumour
		Non-Tumour
		Non-Tumour
		Non-Tumour
		Non-Tumour
		Non-Tumour

Table 5: Simulation results for the technique

D. *Segmentation Results*

The division results are presented in this section and given in table 6. The division is evaluated using true positive rate and segmentation rate.

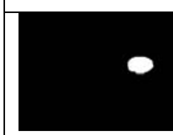
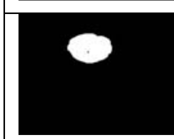
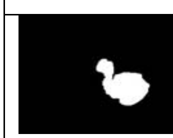
Segmented Image	*True Positive Rate*	*Segmentation Rate*
	1	0.9678
	1	0.943
	1	1
	1	0.91
	0.8347	0.95

Table 6: Segmentation results

E. Performance Analysis

In this section, performance analysis is held out for the technique using evaluation parameters. The values are studied by varying cluster size.

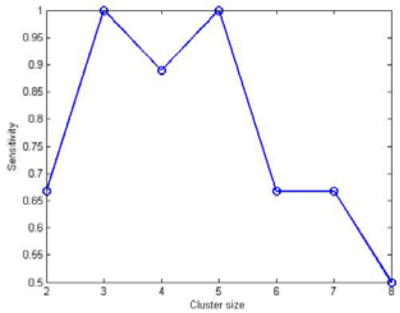


Fig 2: Sensitivity graph for varying cluster

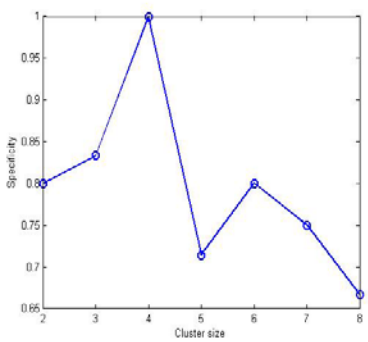


Fig 3: Specificity graph for varying cluster

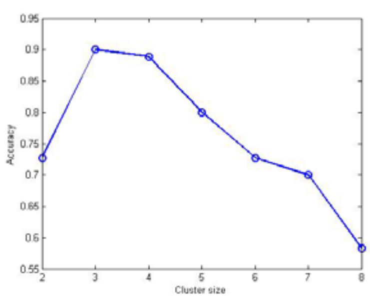


Fig 4: Accuracy graph for varying cluster

Inferences from table 7 and figures 2-4:

- The performance analysis is held out for the technique using evaluation parameters of sensitivity, specificity and accuracy.
- Table 7 gives the TP, FP, FN and TN along with other parameters.
- The results are taken by varying cluster size from cluster size two to eight.
- Figures 2-4 gives the sensitivity, specificity and accuracy graphs for varying clusters.
- Examining the table and figures, we can ensure that the technique gave good evaluation parameter values for all values of cluster size.
- Average sensitivity, specificity and accuracy values came about 0.77, 0.80 and 0.78 respectively for the technique.
- Highest sensitivity, specificity and accuracy values came about 1, 1 and 0.9 respectively.
- The best results were obtained for the cluster sizes 3 and 4.
- It is noticed that a slight drop in performance with increasing clusters (after size >4).

Robustness Analysis

The robustness analysis is borne away by incorporating various noises and getting hold of the evaluation parameter results. The noises considered are salt and pepper noise, Gaussian noise, speckle noise and Poisson noise.

C) Salt and Pepper Noise

Cluster Size	*Sensitivity*	*Specificity*	*Accuracy*
2	0.4286	0.5714	0.5000
3	1	0.7143	0.8010
4	0.667	0.8000	0.7273
5	0.6667	0.7500	0.7000
6	0.5000	0.6667	0.5833
7	0.667	0.8000	0.7273
8	0.4286	0.5000	0.4615

Table 8: Evaluation Results for Salt and pepper noise

C) Gaussian Noise

Cluster Size	*Sensitivity*	*Specificity*	*Accuracy*
2	0.6667	0.7500	0.7000
3	0.667	0.8000	0.7273
4	0.5000	0.6667	0.5833
5	0.5000	0.6667	0.5833
6	0.4286	0.5714	0.5000
7	0.4286	0.5000	0.4615

8	0.4286	0.5000	0.4615

Table 9: Evaluation Results for Gaussian noise

C) Speckle Noise

Cluster Size	*Sensitivity*	*Specificity*	*Accuracy*
2	0.667	0.8000	0.7273
3	1	0.7143	0.8000
4	0.6667	0.7500	0.7000
5	0.6667	0.7500	0.7000
6	0.5000	0.6667	0.5833
7	0.4286	0.5714	0.5000
8	0.4286	0.5714	0.5000

Table 10: Evaluation Results for Speckle noise

C) Poisson Noise

Cluster Size	*Sensitivity*	*Specificity*	*Accuracy*
2	0.6667	0.7500	0.7000
3	0.667	0.8010	0.7273
4	0.5000	0.6667	0.5833
5	0.4286	0.5714	0.5000
6	0.4286	0.5714	0.5000
7	0.4286	0.5000	0.4615
8	0.4286	0.5000	0.4615

Table 11: Evaluation Results for Poisson noise

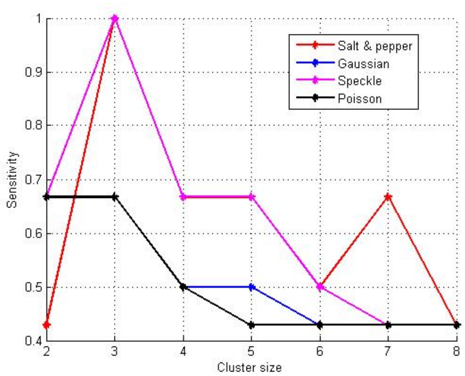


Fig 5: Sensitivity graph for varying cluster for all noise

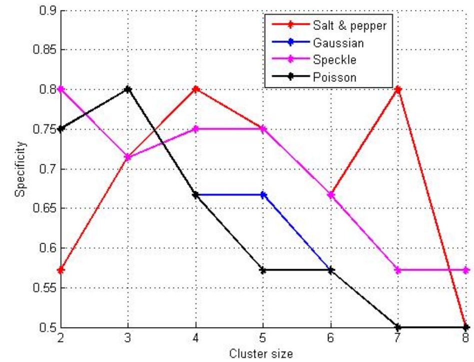


Fig 6: Specificity graph for varying cluster for all noise

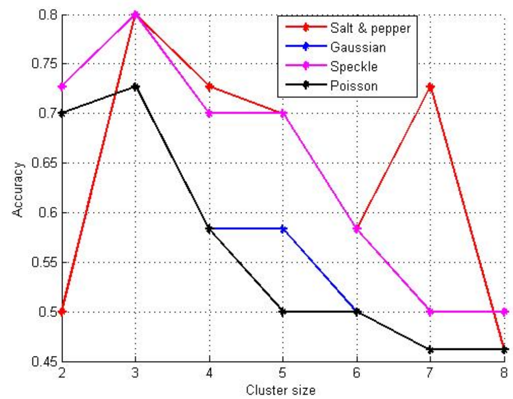


Fig 7: Accuracy graph for varying cluster for all noise

Inferences from figures 5-7 and tables 8-11:

- The robustness analysis is borne away by incorporating various noises and getting hold of the evaluation parameter results of sensitivity, specificity and accuracy.
- The noises considered are salt and pepper noise, Gaussian noise, speckle noise and Poisson noise.
- The evaluation parameters obtained from salt and pepper noise are given in figure 5 and table 8. Similarly, evaluation parameters obtained for Gaussian noise are presented in figure 6 and table 9. Evaluation parameters obtained for speckle noise are given in figure 7 and table 10 and evaluation parameters obtained for Poisson noise is presented in figure 8 and table 11.
- The results are studied by varying cluster size from cluster size two to eight.
- Analyzing the tables and figures, we can infer that the technique performed well in the presence of noise sighting at good robustness.
- Average sensitivity, specificity and accuracy values came about 0.62, 0.68 and 0.64 respectively for salt and pepper noise. Average sensitivity, specificity and accuracy values came

about 0.51, 0.64 and 0.58 respectively for Gaussian noise. Average sensitivity, specificity and accuracy values came about 0.51, 0.62 and 0.56 respectively for speckle noise. Average sensitivity, specificity and accuracy values came about 0.77, 0.80 and 0.78 respectively for the Poisson noise.

- Total average in case for all noise came about 0.57 for sensitivity, 0.66 for specificity and 0.61 for accuracy.
- Highest sensitivity, specificity and accuracy values came about 1 (for salt and pepper and speckle noise), 0.801 (for Poisson noise) and 0.801 (salt and pepper noise) respectively.
- It is observed that best results for cluster size three and we can likewise witness a dip in public presentation for increasing cluster size (after size 3).
- The results demonstrate the validity of the proficiency.

F. *Comparative Analysis*

This section covers comparative analysis with other prominent techniques. The section consists the comparison to our earlier paper as well as to other conventional techniques.

I. With Earlier Paper

Here, the technique discussed (Fuzzy Bisector, K-MEANS and F-PSO based) is compared to our earlier technique (Expectation Maximum and Neural network based). In table 12 and figure 8, earlier technique is denoted by ‘A’ and this composition technique is denoted by ‘B’.

	Sensitivity		Specificity		Accuracy	
Cluster Size	A	B	A	B	A	B
2	0.66	0.667	0.5294	0.8000	0.70	0.7273
3	1	1	1	0.8333	0.8889	0.9000
4	1	0.8889	0.7143	1	0.8000	0.8889
5	1	1	0.7143	0.7143	0.8000	0.8000
6	0.667	0.6667	0.5833	0.8000	0.70	0.7273
7	0.5000	0.667	0.5000	0.7500	0.5833	0.7000
8	0.4286	0.5000	0.5714	0.6667	0.5000	0.5833

Table 12: Table showing comparative analysis with earlier paper

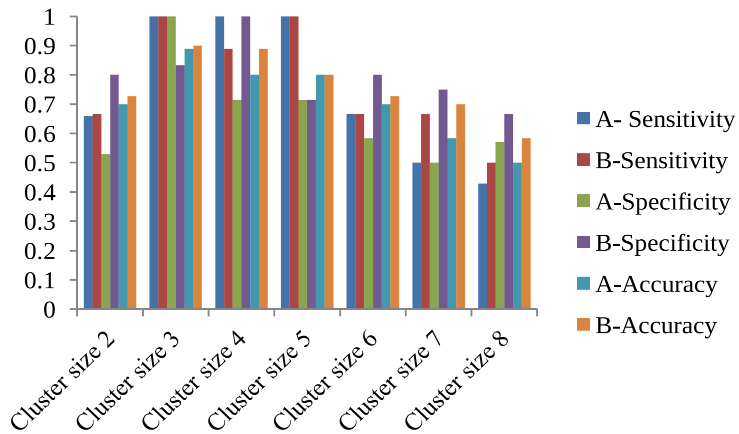


Fig 8: Chart for comparative analysis with earlier paper

Inferences from figure 8 and table 12:

- The analysis is borne out by comparing the technique discussed (Fuzzy Bisector, K-MEANS and F-PSO based) with our earlier technique (Expectation Maximum and Neural network based).
- The evaluation parameters employed are sensitivity, specificity and accuracy.
- The results are taken by varying cluster size from cluster size two to eight.
- Examining the table and figure, we can understand that the technique performed better than the old technique.

Technique	Sensitivity	Specificity	Accuracy
Region growing based [22]	0.44	0.48	0.46
Adaptive Region growing based [22]	0.54	0.62	0.58
Expectation Maximum and Neural network	0.66	0.75	0.71

based (earlier paper)			
Fuzzy Bisector, K-MEANS and F-PSO based (this paper)	0.77	0.80	0.78

Table 13: Comparative analysis table with conventional techniques

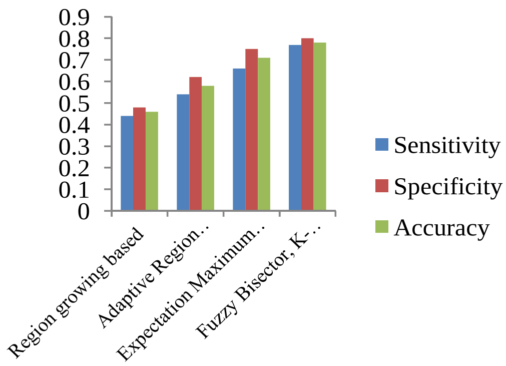


Fig 9: Chart showing comparative analysis with conventional techniques

Inferences from figure 9 and table 13:

- The comparative analysis is carried out by comparing the technique discussed (Fuzzy Bisector, K-MEANS and F-PSO based) with region growing base technique [22], adaptive region growing technique [22] and our earlier technique (Expectation Maximum and Neural network based).
- The parameters of sensitivity, specificity and accuracy are used for valuation.
- Analyzing the tables and figure, we can infer that the technique came out with better results (sensitivity of 0.77, specificity of 0.80 and accuracy of 0.78) when compared with other techniques.

G. Computational Analysis

The computational details about the technique and about the images are presented in table 14 given below:

Number of tumor images	28
Number of non-tumour images	12
Number of training images	30
Number of testing images *Here it is such that the training and testing images are different.	10
Initial weight range	[-1,1]
Number of iteration	100
Convergence value	0.1
Training time: *Computational time required for algorithm training computational time for segmenting each scene	8.234s
Operator time per segmentation	0.4238s
Human operator time required to complete segmentation *Human operator time required to complete segmentation =operator training time+ algorithm training	8.6578s

Table 14: Computational details

Conclusion

The tumor detection technique using Fuzzy Bisector based K-means clustering (FB-K means) and Fractional PSO (F-PSO) based Neural Network is analyzed and valued in a more elaborate and in-depth manner. More simulation results including that of skull stripping, histogram equalization, segmentation and classification are added for more reason. Segmentation efficiency is added in a detailed manner, extracting the true positive rate and segmentation rate. Thorough experimental analysis is held out by detecting out the evaluation parameters including true positive, false positive, false positive, false negative, sensitivity, specificity and accuracy varying cluster sizes of 1 to 8. Average sensitivity, specificity and accuracy values came about 0.77, 0.80 and 0.78 respectively, for the technique and highest sensitivity, specificity and accuracy values came about 1, 1 and 0.9 respectively. Robustness analysis is borne out to find out noise suppression ability under various sorts of disturbances such as salt and pepper, Gaussian, speckle and Poisson. Total average in case for all noise came about 0.57 for sensitivity, 0.66 for specificity and 0.61 for accuracy. Comparative analysis is also borne away by comparing to conventional techniques. Computational analysis is also done for finding efficiency based on fourth dimension of computation and other training dates. Training time came about 8.234s. The analysis and evaluation infers that the technique performed well by obtaining good evaluation parameters. The technique also achieved good robustness and efficiency.

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