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Analysing MRI Brain Images Using Fuzzy C–Means Algorithm

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Abstract : :Data mining techniques are applied to Medical image processing for the identification of significant diseases in medical images like Magnetic Resonance Imaging (MRI), mammogram and some other images. A number of Data Mining (DM) algorithms are utilised for the analysis of such diseases. Particularly, this work analyses about the use ofclustering technique and some pre-processing methods applied in the prediction of disease in MRI brain images inthe medical domains. The very famous clustering algorithm Fuzzy C-Means (FCM) is one among the effective algorithm which is used to determine the segmented part of any medical images. This research work is carried out to analyse the MRI brain images to find the tumour affected regions in order to find the classification of MRI images via experimental results. The results produced by this algorithm are proved in an authenticated manner for a set of MRI images. The FCM algorithm is tested with different set of input images and identified cancer area based on its intensity in the MRIimages. The analysis is carried out to determine the highly affected area in the MRI images. The significant area identified through clustering is used for further medical applications by the physicians. The FCM algorithm isanalysed based on their clustering result quality.

Keywords : MRI Medical images, Fuzzy C-Mean Algorithm, Noise Removal Techniques, Image Segmentation.

1. INTRODUCTION

Data mining (DM) techniques are applied in the medical domain for analysing the data which support for the decision making process and to give treatment for the patients using computational techniques. Development of data mining applications and its implications are manifested in the areas of data management in healthcare administrations, epidemiology, patient care and intensive care systems, significant data analysis for information extraction and automatic identification of unknown subjects which are extracted from the hidden dataset. The hierarchical genetic system for segmentation of multi spectral human brain discussed the process view of medical data is the visualization of body parts, tissues, or organs, for use in clinical diagnosis, treatment and disease monitoring. Imaging techniques take in the fields of radiology, nuclear medicine and optical imaging and image-guided interference [23]. Medical data analysis techniques are presented in many research works using the region of interest (ROI) pre-processing technique [14]. DM has various techniques such as Classification, Clustering, Prediction, Association Rules, Decisions Tress, and Neural Networks [13, 36] which are applied in the Medical image processing.

DM is used to identify the variations of the human brain functional process according to its similarity measures [36]. The Brain MRI is provided signal variations of the human brain and its transmissions in the instance while observing the person. The variations on the obtained image signals and its values are shown the activeness, an abnormality of the human brain functionality [44] analysis [24]. The Review of methods for solving the EEG inverse problem solved localization of activity maxima and the mean time edges are significant local changes of intensity in a research work [15]. Edges typically take place on the boundary between two different regions in an image using mean algorithms.

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The Fuzzy C-Mean (FCM) algorithm is an unsupervised method applied and its results are discussed in Magnetic resonance imaging (MRI) brain image [40]. The clustered object relationships are determined with different cluster levels. The similarity and variations are identified. The high level variations are identified after the noise removed original data and then it is clustered. This work has been carried out to segment the frames from the captured MRI file and cluster the same using Fuzzy C-Mean (FCM) algorithm.

The organization of this paper is structured as follows. Section II discusses about the related work from various previous research papers. Section III explores about the methodology used for this work which covers pre-processing techniques and Fuzzy C-Mean clustering algorithm. The results identification of images in intensity based on pixels in MRI data and performances of clustering algorithm is demonstrated in section IV. Finally, the work is concluded and findings are given in section V.

2. RELATED WORK

The Comparative study of different clustering algorithm is analyzed as part of this session. In brain tumor detection using color-based k-Means clustering segmentation is presented in [25, 37, 45]. In the fuzzy clustering algorithms tissue differentiation in MRI of ophthalmology uses for the segmentation techniques, a color based segmentation technique (*k*-Means clustering algorithm) used to track tumor objects in MRI brain images. In these color based segmentation algorithm with k-Means are used to detect change a given gray-level image. A color space image and then single the location of tumour objects from other items of an MRI brain image by using k-Means clustering and histogram-clustering analysis. The method can excellently complete segmentation of MRI brain images which identified from the results in their papers. They finally concluded that the k-means clustering and histogram clustering, thus making it efficient and very easy to implement to analysis the brain MRI images.

Automatic image pixel clustering with an improved differential evolution in [26] is explored by Swagatamda set al. In this work, an evolutionary fuzzy clustering algorithm for regular combination of the pixels of an image is partitioned into different uniform regions. The algorithm does not need a previous knowledge of the number of clusters. The fuzzy clustering job in the intensity space of an image is formulated as an optimization problem. An improved variant of the differential evolution algorithm has been used to determine the number of logically occurring clusters in the image as well as to improve the cluster centers. A research has a comparison between the algorithms genetic fuzzy clustering technique and the classical fuzzy c-means algorithm. They are supremacy of the future technique in terms of speed, accuracy and robustness.

Omranet al. carried out work in [27][33],in which particle swarm optimizer algorithm introduced the centroids of a user précised number of clusters, where each cluster groups together with similar image primitives. To illustrate its wide applicability, the input image classifier has been applied to synthetic, MRI and satellite images. The results show that the PSO image classifier performs better than state-of-the-art image classifiers namely, *k*-Means, Fuzzy C-means, K-Harmonic means and Genetic Algorithms in all measured criteria. The influences of different values of PSO control parameters on performance are also clarified. A.Naveen and T. Velmurugan [28] carried out an article titled as "Identification of calcification in MRI brain images by k-Means algorithm". They discussed various data mining techniques in boundary detection and outlier analysis is an main model for pre processing the dataset. The boundary considers only pixels lying on and near edges and use of gradient or Laplaci an to preliminary processing of images. An outlier is a pattern which is different with respect to the rest of the patterns in the data. They identifying the calcification in MRI brain image is perfectly done by simple k-Means algorithm. Also, it is clear that the number of pixels are differ when the numbers of clusters. Therefore, modified versions of the simple k-Means algorithm are requiring for work to get the better result.

M. A. Balafar et al. discussed about review of brain MRI image segmentation methods in their research work [29]. A review of the methods used in brain segmentation. The review covers imaging modalities, magnetic resonance imaging and methods for noise reduction, inhomogeneity correction and segmentation. They discussed with brain MRI segmentation is a challenging task and there is a need for future research to improve the accuracy, precision and speed of segmentation methods.A research work titled as "An Adaptive Mean-Shift Framework for MRI Brain Segmentation" is carried out in [30]. They analyze the automated scheme for MRI brain segmentation. An adaptive mean-shift method is used in order to categorize brain voxels three main tissue types white matter, gray matter, and Cerebro-spinal fluid. The MRI image space is signified by a high dimensional feature space that includes multimodal intensity features as well as different features. The proposed method is validated on single and multimodal datasets, for both simulated and real MRI data. It is shown to implement well in comparison to other state-of-the-art methods without the use of a preregistered statistical brain atlas.

A research paper by Keh-Shih Chuang et al. discussed about Fuzzy c-means clustering with spatial information for image segmentation [31]. They are present at FCM algorithm that incorporates spatial information into the membership function for clustering. This method is a powerful method for image segmentation and works for both single and multiple-feature data with spatial data. The proposed methods are a spatial FCM that incorporates the spatial information into the membership function to improve the segmentation results. The membership functions of the neighbors centered on a pixel in the spatial domain are enumerated to obtain the cluster distribution statistics. These statistics are transformed into a weighting function and incorporated into the membership function. This neighboring effect reduces the number of spurious blobs and biases the solution toward piecewise homogeneous labeling. The new method was tested on MRI images and evaluated by using various cluster validity functions. Preliminary results showed that the effect of noise in segmentation was considerably less with the new algorithm than with the conventional FCM. A modified FCM algorithm for MRI brain image segmentation [32] explored by Abolfazl Kouhi et al. The conservatively standard FCM algorithm is sensitive to noise because of not taking into account the spatial information. To overcome this problem, a modified FCM algorithm for MRI brain image segmentation is presented in their paper. They projected algorithm is formulated by modifying the objective function of the standard fuzzy c-means algorithm to enhance the noise immunity. The results on both synthetic and real images which dishonored with noise specify that they proposed algorithm is more accurate and robust to noise than the standard FCM algorithm [32]. Experimental results show that the proposed method is effective and more robust to noise and other artifacts than the conventional FCM algorithm in image segmentation. This section discusses about so many algorithms and techniques for image segmentation in medical images in the data mining domain. Among these, clustering methods plays a vital role and solve many complex problems in medical imaging.

3. METHODOLOGY

To analyze any kind of data, it is required that some standard methods to find the usefulness of the data set. This research work also has some methods for preprocessing and one method for segmentation. The images are preprocessed first to remove the noises and the output is segmented by FCM algorithm. The preprocessing is done by using the methods Region of Interest [39], inverse method and edge detection by boundary method in the input images. The main objective of this research work is to predict the performance of the FCM clustering algorithm based on intensity in MRI brain images. The various methods used in this work are elaborated as follows.

A. Image Pre processing

The preprocessing is an enhancement of the image data that suppresses unwanted distortions or enhances some images features important for further processing [9]. It is one of the riskiest steps in a DM process which deals with the training and transformation of the original images dataset. Data preprocessing methods are separated into following categories data cleaning, data integration, data transformation and data reduction [1, 2]. The steps involved in this work are applying preprocessing techniques [43] Region of Interest (ROI), Inverse Method and Edge Detection for boundary from the image.

B. Region of interest (ROI)

Once a set of bounds was chosen for spatially constrained collection clustering, the effects of this method were matched to four commonly used Region-of-Interests [24]. The ROI is a portion of an image that you want to filter or perform some other operation on. A defining by creating a binary mask, which is a binary image that is the same size as the image you want to process. In the mask image, the pixels that describe the ROI are set to 1 and all other pixels set to 0.

The derivation of the approximation formula is divided into two parts:

1. The variance of a single pixel value is derived without the use of the sinogram data; and
2. The variance of an arbitrary ROI is derived based on the mean pixel variance within the region and the correlation between pixels in the ROI. These formulas are derived in general and are then applied to the brain images [34, 12].

First a study Region of Interest with *n* pixels in a pre-processed image, the mean value is P of the pixels, and similarly the P in the Region of Interest is

$$P = \frac{1}{n}\sum_{i=1}^{n} f_i \tag{1}$$

Where f_i ; are the individual pixel values, the variance of the ROI value is

$$X(P) = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n} Cov(f_i, f_i)$$

or

$$X(P) = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n} \rho_{i,i}\sqrt{X(f_i).\, X(f_i)} \tag{2}$$

Where Cov is covariance and ρ_{ij} is the correlation coefficient between pixel values *i* and *j* within the ROI. X (f_i) can be determined from independent approximations of the pixel variance values and the inter pixel correlation values. Let $\hat{V}$ be the Average pixel variance within the ROI, for a small region, $\hat{V}$ can be approximated by the variance of the central pixel, and large regions, $\hat{V}$ can be estimated by averaging variance estimates from several pixels distributed throughout the region.

$$X(P) = \frac{\hat{V}}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n} \rho(dis_{i,\, j}). \tag{3}$$

The above assessment formula for the variance of a particular pixel, and the correlation coefficient ρ_{ij} is approximated by a function ρ(dis) that is the mean correlation between pairs of pixels separated by distance dis. inserting into (2) the approximations of $\hat{V}\ f$ or X (f_i) and ρ(dis $_{i,j}$) for $\rho_{i,j}$ produces [16, 17].

C. Inverse Method

Let A be an invertible $m \times n$ matrix. Suppose that a sequence of elementary row-operations reduces A to the identity matrix. Then the same sequence of elementary row-operations when applied to the identity matrix yields A^{-1}.

Definition : Given a m X n real matrix A and a *n* X *m* matrix pseudo inverse A+ are defined as follows

$$\begin{aligned} AA+A &= A \\ A+AA+ &= A+ \\ (AA+)T &= AA+ \\ (A+A)T &= A+A \end{aligned}$$

Pseudo inverse by Singular Value Decomposition (SVD) is defined as that supposes A is *m* X *n* matrix. If $m < n$, connect the row of 0 and make the size $m = n$, a priori. Here, $m \geq n$.

D. Boundary Detection Method

This method has the skull-brain boundary as an interface of two regions. It is well-known, at the interface of second interfacial waves propagate along the boundary detection method. The amplitude of such waves remains constant along the interface boundary and decay exponentially in a path perpendicular to the interface. In a plane geometry, at the interface of water, air, hydrodynamic surface waves propagate along the interface with constant amplitude [9], but decay exponentially in a direction perpendicular to the interface [11, 7]. Hydro magnetic interface waves propagate in a similar way in a plasma-plasma interface embedded in a magnetic field [10]. We construct, use of a related property to identify the boundary between skull-brain interfaces. At the boundary, made of white pixels, the intensity value will be $\approx$ 255 in a grayscale image. Where, A is an arbitrary constant, $\Delta f(x, y) = 255 - f(x, y)$, and $f(x, y)$ is the intensity value of the input image at the coordinate points (x, y). Therefore, R will be very large at the boundary, where $f(x, y) \approx 255$ and will be small at the points away from the boundary. Hence, by computing the value of R and traversing the coordinates (x, y) where R (x, y) gives highest value, the boundary of the brain skull can be identified and extracted [21, 19]. Therefore, the boundary can be detected by using the resonance function

$$\mathrm{R(X, Y)} = \mathrm{A}\partial^{1/\Delta f(x/y)} \tag{4}$$

In MRI of head scans, two boundaries prominently appear. The inner boundary is the brain-Cerebro spinal flui (CSF) interface, and the outer boundary is the CSF-Skull boundary. If we are able to detect the inner boundary then the brain portion can be extracted easily. To detect the inner boundary we start computing the resonance function R from the midpoint of each row of the middle slice [20, 46]. Hence, identifying the brain area in the center slice is easy. The midpoint of each row is computed by dividing the total width and height of the image by 2.

$$\text{midx} = \text{image\_width}/2 \tag{5}$$

$$\text{midy} = \text{image\_height}/2 \tag{6}$$

The boundary will be formed by analysing the value of R at 5 co-ordinate points at each row in both left and right hand side from the middle. The points that are not close to the innermost boundary are discarded. The inmost contour, thus formed is the boundary of the brain. In any MRI brain volume, the center slice contains brain as an only largest region and is the largest brain portion of the entire volume. The mark of the previous slice is used as a reference to extract brain in the current slice.

E. The Fuzzy C-Mean Algorithm

Fuzzy C-Mean is an unsupervised clustering technique that has been applied to the extensive range of problems involving feature analysis, clustering and classifier design [22, 38]. FCM has a broad domain of applications like image analysis, agricultural engineering, medical diagnosis, geology, astronomy, chemistry, shape analysis, and target recognition [5, 8]. With the improvement of the fuzzy system, the fuzzy c-means clustering system based on Ruspini fuzzy clustering theory was proposed in 1980s [35, 39]. This algorithm is examined to evaluate based on the distance between the various input data points [3, 4]. The clusters are formed according to the distance between data points and cluster centers are formed for each cluster. The method FCM is a method of clustering which allows one piece of data to belong to more than two clusters. This technique is frequently used in pattern recognition. It is based on minimization of the objective function follows

$$Jm = \sum_{i=1}^{\mathrm{N}} \sum_{j=1}^{\mathrm{C}} u_{ij}^{m} \| xi - c_j \|^2, 1 \le m < \infty \tag{7}$$

where m is any real number greater than 1, I_{ij} is the degree of membership of x_i in the cluster j, D_i is the ith of d-dimensional measured data, S_j is the d-dimension center of the cluster, $\|*\|$ is any norm expressing the similarity between any measured data and the center. Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership uij and the cluster centers c_j by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{\mathrm{S}} \left[\frac{\| \mathrm{D}_i - \mathrm{S}_j \|}{\| \mathrm{D}_i - \mathrm{S}_k \|} \right]^{\frac{2}{m-1}}}, sj = \frac{\sum_{i=1}^{\mathrm{N}} \mathrm{I}_{ij}^{m}, x_i}{\sum_{i=1}^{\mathrm{N}} \mathrm{I}_{ij}^{m}} \tag{8}$$

This iteration will stop

When $\max y \left\{ I_{ij}^{(k+1)} - I_{ij}^{(k)} \mid \right\} < \xi$

Where ξ is a termination criterion between 0 and 1, whereas k is the iteration steps. This procedure converges to a local minimum or a saddle point of Jm. The algorithm is composed of the following steps:

Step 1: Initialize $I = [I_{ij}]$ matrix, $I(0)$

Step 2 : At k-step: calculate the centers vectors $S(k) = [s_j]$ with $I(k)$

Step 3 : Update $I(k)$, $I(k + 1)$

Step 4: If $\| I(k + 1) - I(k)\| < \hat{\imath}$ then STOP;

Otherwise, return to step 2.

In this algorithm, data are bound to each cluster by means of a membership function, which represents the fuzzy behavior of the algorithm [6, 9].

In this research work, it is focused on tumor detection by identifying an intensity area in MRI data are taken for analysis. The algorithm is implemented in MATLAB R2008a software. The pre-processing work is done by using the region of interest (ROI), Inverse Method and Edge detection method for the extraction of the input data. After pre-processing the images, they applied to find the clusters by using FCM technique. The number of clusters produced by FCM is 3, 4, 5, and 6.

F. Proposed Methodology

The sequential steps of the methodology used in this work are depicted in the figure 1. The input image is MRI brain image and the output is a segmented image produced by FCM algorithm.

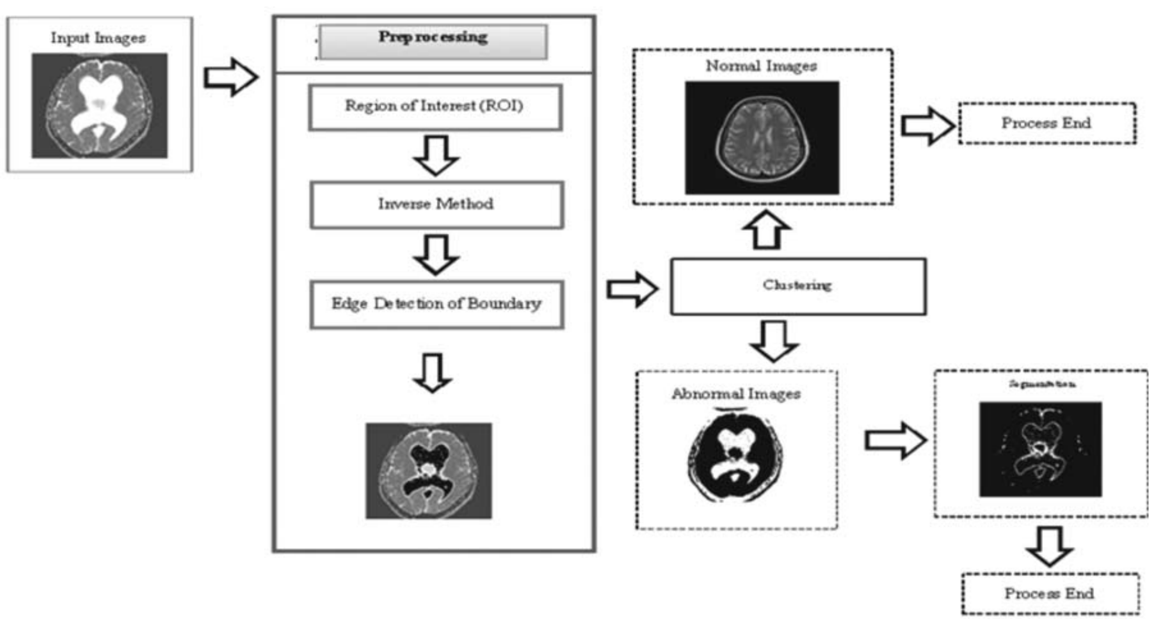

Fig. 1. Proposed system workflow.

The steps involved in clustering the MRI data by the FCM algorithm are given below.

Step 1: Given the original image for preprocessing

Step 2: Apply ROI covariance method

Step 3: Apply Inverse method to identify the appropriateness of the image

Step 4: Use Boundary method to detect edges.

Step 5: Segment the image using FCM

Step 6: Identify normal and abnormal images by means of clustering

Step 7: If the image is a normal terminated process and take the next image

Step 8: If the image is abnormal, then segment the image based on the intensity

Step 9: Find the number of pixels in the abnormal part of the image

Step 10: Summarize the results of different images and put it into the table

G. Experimental Data

Totally 40 images are taken for analysis in this research, which belong to three categories: normal, benign and malignant. The source data set contains 9 normal images, 11 benignstages and 20malignantstages. But this research has been done by taking only 25 images. Only some the benign and malignant images are taken for analysis. The MRI brain images are collected from Swamy Vivekananda Diagnostic Centre (SVDC) - LabatArumbakkam, Chennai indwaraka doss goverdhan doss Vaishnav college campus. The Data are indicated normal and an abnormality status of the MRI brain images are marked by SVDC Lab. The taken experimental data are shown in figure 2.

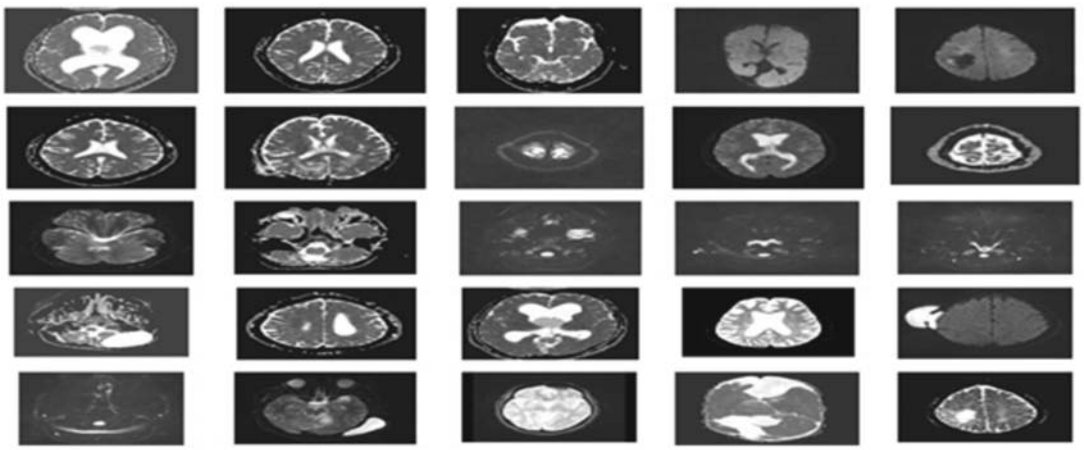

Fig. 2. Input MRI Brian Images.

H. Data Pre-processing

Experimental Data is highly susceptible to noise and inconsistency. The quality of data disturbs the DM results. In order to develop the quality of the consequently and data on the mining outcomes, raw data is pre-processed so as to improve the efficiency and ease of the mining method. The result of pre-processing is shown in figure 3. The preprocessing was done by using three techniques, namely like ROI, inverse method and edge detection method. The ROI method finds the areas of images based its intensity. The inverse method is used to convert the black colors into white and white color into black color, using the values 0 to 256.The edge detection method fixes the boundary that fit for the image clustering by FCM algorithm.

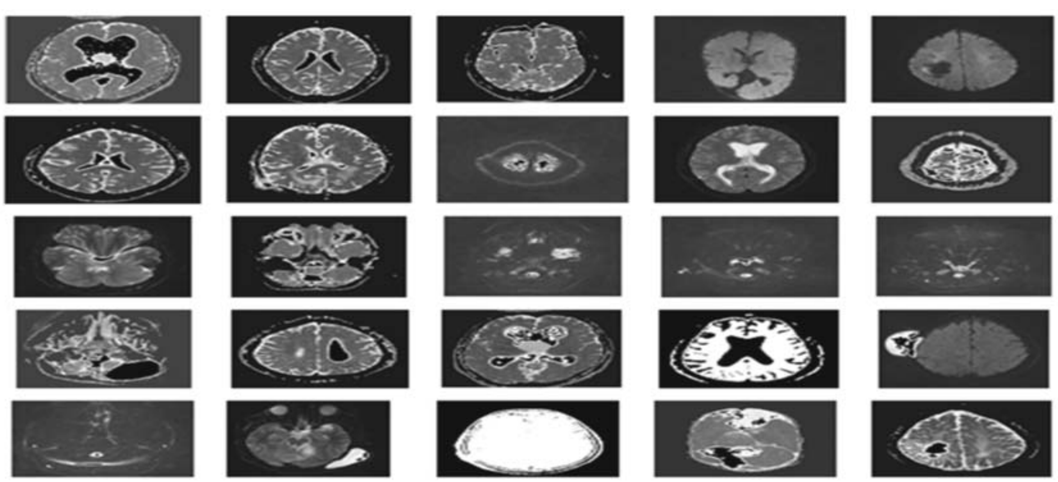

Fig. 3. Result of Preprocessing MRI Brian Image.

4. RESULTS AND DISCUSSION

The output of preprocessing the images are taken as input and the same is extracted by FCM algorithm to find the tumor area via its clustering (Segmentation). During the clustering process, less number of clusters is consideredfor producing the output based on the intensity of images. There is no clear output in clustering the images by one, two and three clusters. After the fourth cluster alone it is obtained a reasonable result by the processing work by FCM. The first 3 clusters are not having any significant results. For example, the clustering results of one of the images is given in the figures 4 (*a*) to 4 (*f*). From these figures, it is evident that there is no clear result produced by the algorithm in the first three clusters. After the fourth cluster, it is clear that the tumor area is shown in different colors. The number of white color and black color pixels based on the intensity is given in table 1.

Fig. 4 (*a*). Output of FCM algorithm in Cluster 1

Fig. 4(*b*). Output of FCM algorithm in Cluster 2

Fig. 4(c). Output of FCM algorithm in Cluster 3

Fig. 4(*d*). Output of FCM algorithm in Cluster 4

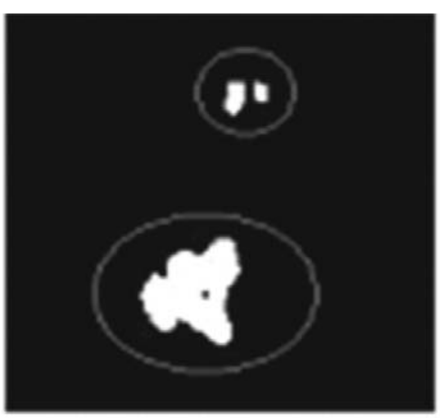

Fig. 4(*e*). Output of FCM algorithm in Cluster 5

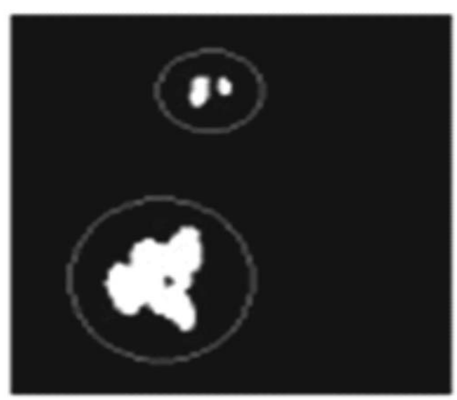

Fig. 4(*f*). Output of FCM algorithm in Cluster 6

Table 1. Result of FCM algorithm based on its intensity (Number of Pixels)

Cluster-1		*Cluster-2*		*Cluster-3*		*Cluster-4*		*Cluster-5*		*Cluster-6*		*Run Time in Milliseconds*
				No of Pixels								
B	***W***	***B***	***W***	***B***	***W***	***B***	***W***	***B***	***W***	***B***	***W***	
67165	194979	236449	25695	220674	41470							57810
68202	193942	242209	19935	215722	46422	260299	1845					11891
71077	191067	251126	11018	240225	21919	225822	36322	260326	1818			15078
71723	190421	252983	9161	246593	15551	235074	27070	243969	18175	260378	1766	21485

The intensity based segmented number of pixel is shown in table 1,where B indicatesthat they are black color pixels, W indicatesthat they are white color pixels. From the figures 4 (*d*) to 4 (*f*), the tumor affected regions are identified. The affected regions are shown and marked in red color.Figures 5 to 7 are the results of output of FCM algorithm in 4th, 5th and 6th clusters respectively for 25 input images. Table 2 shows that the number of pixels in 4th, 5th and 6th clusters. The computational time of each and every cluster are given in the same table. The sum of the black and white color pixels is equal in all the three categories. For example, the sum of black and white pixels for the image 1 in cluster 4 is 262144, which is same in the clusters 5 and 6 also. The figures 8 to 10 are performance of FCM algorithm in 4th, 5th and 6th clusters respectively. The computational time in milliseconds for each and every cluster is also calculated and shown the same table 2. Figures 8 to figure 10 are shown the performance of FCM algorithms based on the computational time. Table 2 have total runtime for all 25 images, in which the minimum time taken by FCM is available for the cluster 5. Hence, it is not require to continuing the clustering work of the images after the 5th cluster. Figure 11 shows that the performance of FCM by its runtime.

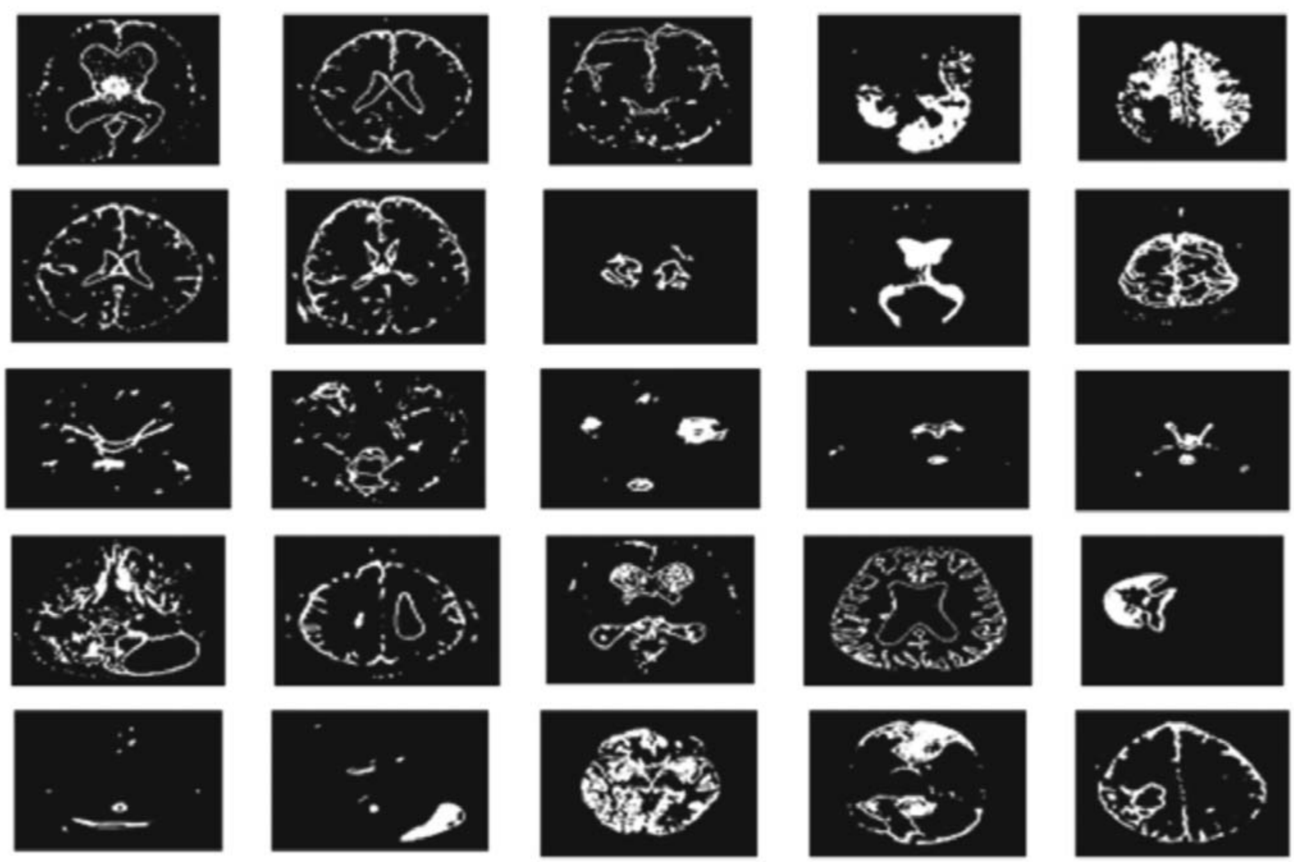

Fig. 5. The output of Cluster 4 .

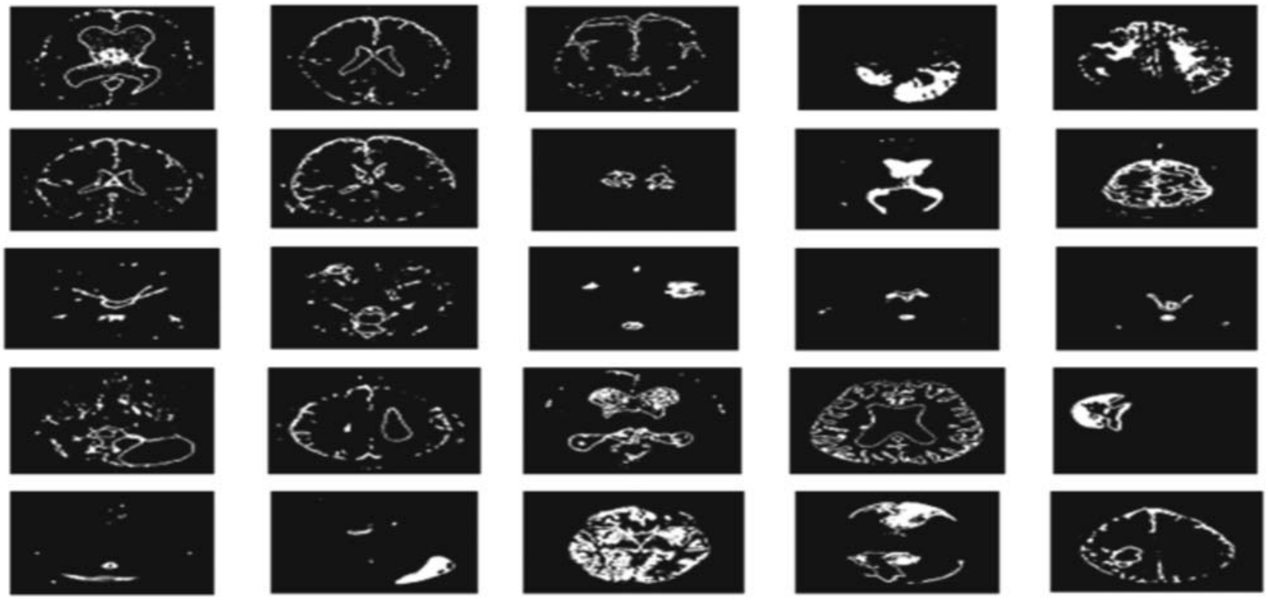

Fig. 6. The output of Cluster 5.

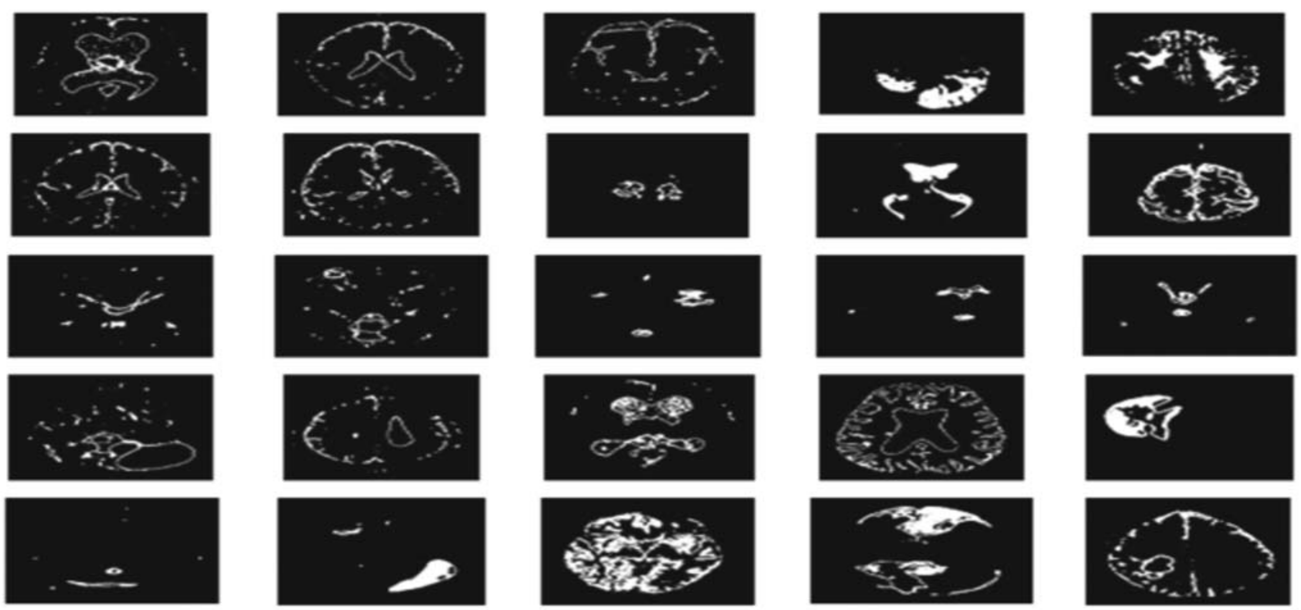

Fig. 7. The output of Cluster 6.

Table 2. Results of 4th, 5th and 6th Cluster

Input Images	*Cluster 4* No of Pixels B	W	Run Time in Milli seconds	*Cluster 5* No of Pixels B	W	Run Time in Milli seconds	*Cluster 6* No of Pixels B	W	Run Time in Milli seconds
Img1	247709	14435	15055	249056	13088	12570	253100	9044	16549
Img 2	251636	10508	10216	254792	7352	19331	256024	6120	22988
Img 3	252489	9655	10016	255338	6806	19218	256440	5704	23134
Img 4	242371	19773	10084	248777	13367	19239	249750	12394	22943

Input	***Cluster 4***			***Cluster 5***			***Cluster 6***		
Images	***No of Pixels B***	***W***	***Run Time in Milli seconds***	***No of Pixels B***	***W***	***Run Time in Milli seconds***	***No of Pixels B***	***W***	***Run Time in Milli seconds***
Img 5	230763	31381	15376	246617	15527	19323	248393	13751	23258
Img 6	250110	12034	10469	253963	8181	16171	255222	6922	21672
Img 7	245684	16460	17660	250778	11366	15906	253068	9076	21375
Img 8	259484	2660	15657	259969	2175	19432	260182	1962	23630
Img 9	251154	10990	7672	252255	9889	11281	254151	7993	16219
Img 10	250053	12091	12068	250209	11935	15471	253442	8702	21200
Img 11	256340	5804	15142	258533	3611	19176	258975	3169	23147
Img 12	254096	8048	13373	255441	6703	18831	258022	4122	23433
Img 13	257991	4153	13995	259082	3062	18841	259790	2354	21669
Img 14	260283	1861	84930	260406	1738	17782	260839	1305	21959
Img 15	259938	2206	14167	260777	1367	17739	260846	1298	22359
Img 16	240371	21773	10811	253343	8801	17312	256023	6121	23656
Img 17	251627	10517	92230	255118	7026	18390	256833	5311	21925
Img 18	247932	14212	98320	249640	12504	10620	249881	12263	22260
Img 19	246624	15520	93540	247314	14830	16164	250748	11396	20717
Img 20	256668	5476	16047	256687	5457	17955	256725	5419	22160
Img 21	259094	3050	10638	259659	2485	11525	260334	1810	13907
Img 22	254996	7148	10054	255588	6556	17813	255685	6459	23335
Img 23	231338	30806	82380	232085	30059	76200	234201	27943	16728
Img 24	244300	17844	37820	247836	14308	14194	248100	14044	20809
Img 25	249802	12342	85700	253454	8690	16054	253454	8690	20097
Total Run Time			803420			476538			531129

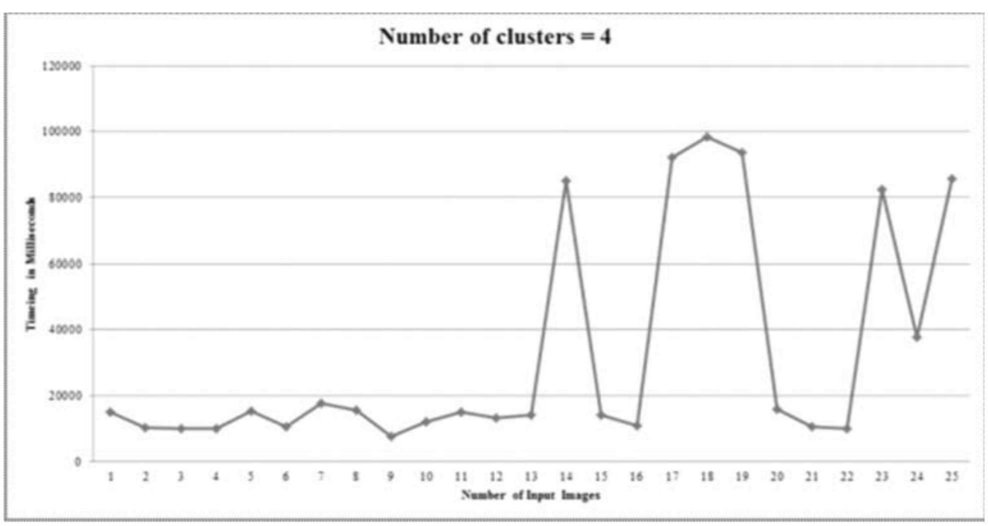

Fig. 8. Performance for Cluster 4.

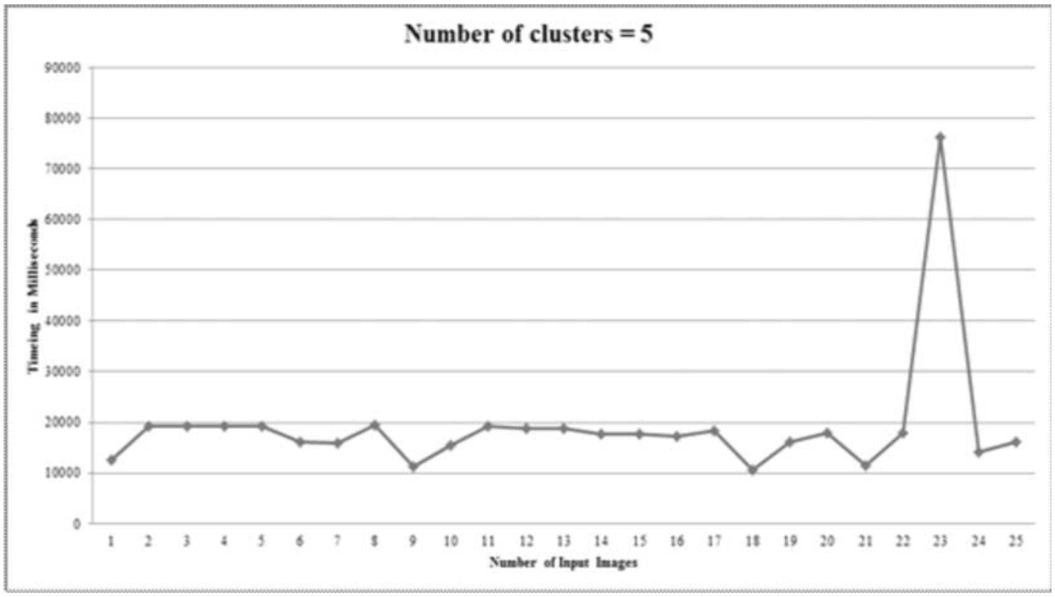

Fig. 9. Performance for Cluster 5.

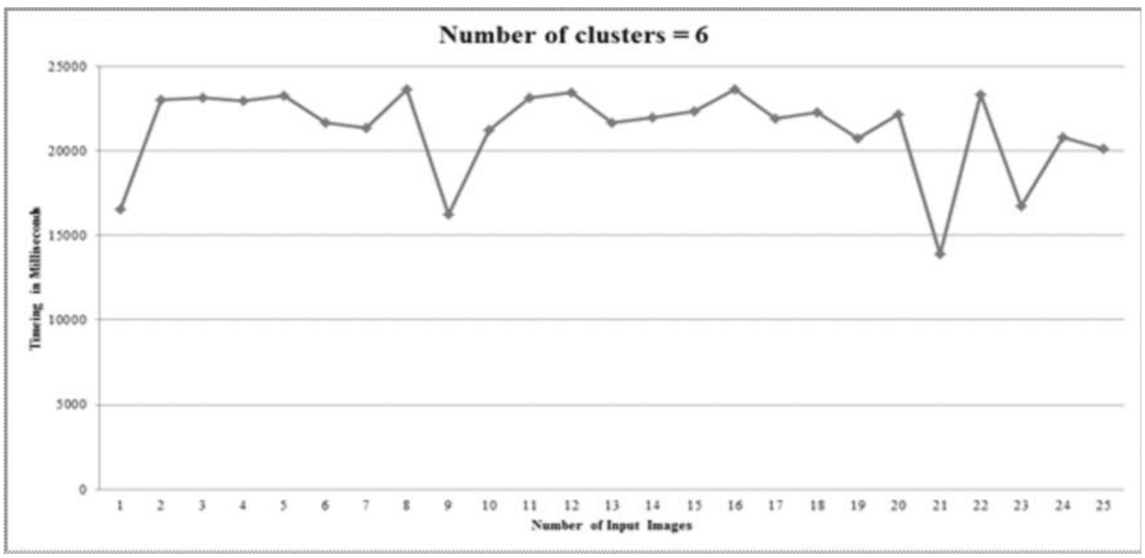

Fig. 10. Performance for Cluster 6.

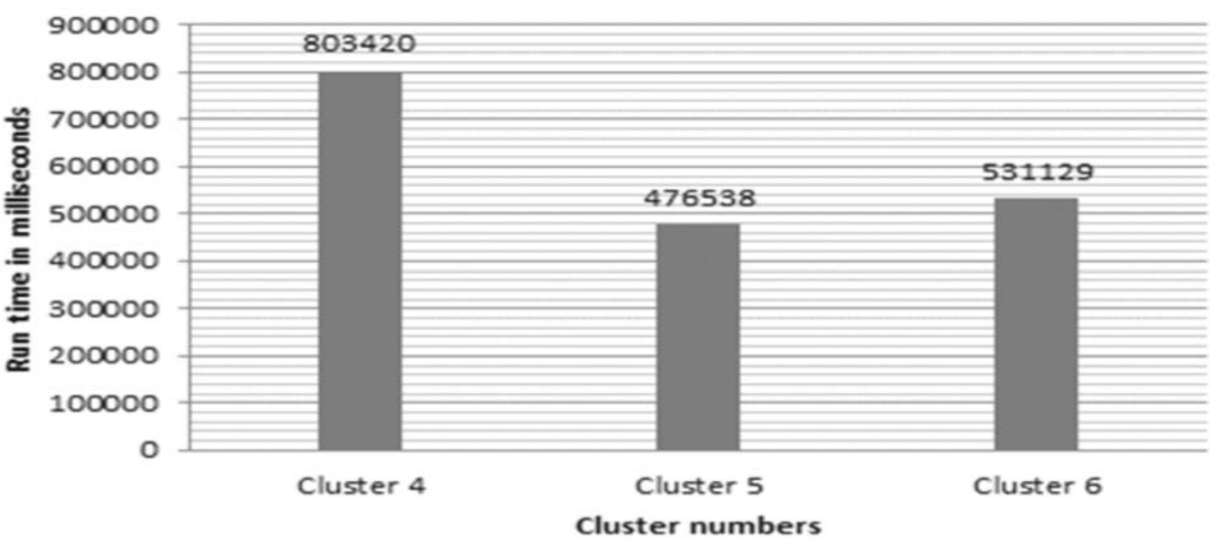

Fig. 11. Performance of FCM by run time.

5. CONCLUSIONS

The DM techniques are applied in various domains in order to analyse the data efficiently. Also, the DM methods perform well in finding the diseases in medical field. In this sequence, the FCM algorithm is applied to find the tumor affected areas in MRI brain images in this research work. To identify the significant affected area of the MRI images, the FCM algorithm gets good result by means of identifying tumor area based on the intensity of images. There are 25 images are given as input to the algorithm as a test case. The normal images are removed from the data set after the processing work. Only the tumor affected images are given as input in this approach. Initially, many images are given as input and taken the affected images alone for the analysis. The results of all images are given to the respective physicians (those who are expert in the field) for the verification purpose, they agreed the results detected by the FCM method is accurate and correct. Hence, this research work concludes that the FCM algorithm performs well in finding tumor affected regions in MRI brain images.

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