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Locating Tumours in the MRI Image of the Brain by using Pattern Based K-Means and Fuzzy C-Means Clustering Algorithm

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Abstract: This paper presents a powerful segmentation method which is the integration of Pattern based K-means also modified Fuzzy C-means (PKFCM) gathering calculation for trademark extraction with versatile gamma amendment which result in better upgraded picture contrast with other existing strategies. In this strategy, the model is selected based on the convolution between the gray level intensity in the small portion of the brain image and the image of the brain tumor. The K algorithm means emphasizing the initial segmentation through proper model selection. Updated membership is obtained using the distances from cluster centroid to cluster data points, until it reaches the best. This Euclidian distance depends on the different characteristics, namely intensity, entropy, contrast, dissimilarity and homogeneity of the coarse image, which only depended on its similarity to conventional FCMs. Then, depending on the upgrade and automatic cluster selection, a sharp segmented image with a red marked tumor is obtained by modified FCM technique. The small deviation of the gray level intensity of normal and abnormal tissue is detected through PKFCM. The performance of the PKFCM method is analyzed through the neural network which provide better regression and less error. The performance parameters show significant results that they are effective in detecting brain tumors based on multiple intensity MRI images of brain.

Keywords: Pattern based K-means and Fuzzy C-means algorithm, Cluster data points, Euclidian distance, FCM, updated membership.

I. INTRODUCTION

In recent decades, effective brain tumor detection in the context of MRI has been a major challenge for medical science. Magnetic resonance technique has a good contrast compared to different techniques. However, an adequate segmentation of brain magnetic resonance imaging is evident to detect anomalies in the brain. As the brain understands the complicated structure so the segmentation of magnetic resonance requires good care and needs to be accurate.Segmentation describes salient image regions to procure by region (s) of interest (ROIs) such as legions, tumors, edema, and necrotic brain imaging tissue [1].

For segmentation of brain image, numerous image processing has been proposed, such as region growth threshold, classifiers, artificial neural networks (ANN), grouping, etc.

Scalar segmentation of images by creating a binary partition of the image intensity is performed according to the threshold. Due to the complexity of the brain tissue structure, the appropriate threshold value is very difficult to achieve. The main disadvantage is that the threshold cannot be applicable for multi-channel images. It also provides spatial characteristics, which makes it susceptible to noise and non-uniform intensity. Also, the threshold restriction also used collectively with other classifier methods, ANN, grouping, etc. Based on some predefined criteria, i.e. intensity and edges information, the linked region of an image is extracted in the growing region [2].

In addition, precise anatomical information is needed to locate single or multiple seed pixels for each region associated with homogeneity is called region growing [3-4]. The main limitation to the region's growth is that the seed point is established through manual interaction. In the Classifier method, you need an errorless pixel classifier for retraining data. Inadequate training and classifier are time-bound and leads to hilarious results [2]. In the cluster technique, Fuzzy c-means (FCM) clustering and expectation maximization (EM) algorithms are most often clusters, due used for clustering. It has several advantages like it extremely useful results for true word applications Like banking, medical etc. it has several advantages, For Example, it takes lots of time in the formation of to which the cost will increase. An ANN is used, and its performance is compared with FCM to segment MR brain images. Conventional FCM, has limitations of long calculation time,

sensitivity to the initial hypothesis (speed, local minima), noise sensitivity is expected and a low (or even no), and noisy point. But for optimal results in this field we must minimize the limitation of the individual methods described here [5].

In this paper we proposed a different technique for the detection of brain tumors through MRI image, based on the combination of K-means model-based and modified FCM (PKFCM). The pattern or gray level selection and noise of FCM method and region growing is reduced. The k-means extension is based on models applied through the position of pixel intensity. Very little Pixel intensity is not avoided, as the model is selected according to the number of gray-level to use and the coarse image. The FCM algorithm is modified based on updated membership and the number of cluster members for the filtered image. Updated membership is based on features such as intensity, entropy, contrast, and homogeneity of the brain magnetic resonance imaging. By choosing the input membership and appropriate output variables together with the set number of functions and clusters, the tumor detection is completed neatly. The total yield is analyzed through the neural network, which is widely accepted in the segmentation field. It is executed to prepare and train the data for the suitable image through the network which has feedforward backpropagation algorithm.

II. METHODOLOGY

A. K-Means Algorithm

Historically, the average K-mean cluster is usually introduced to group a set of data points $\{x_1, x_2, \ldots \ldots, x_N\}$ into clusters K [6]. It has high computational efficiency and can support multidimensional vectors. Therefore, it reduces the minimization measurement distortion of a cost function such as:

$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} b_{nk} \|x_n - c_k\|^2$$

$$b_{nk} = \begin{cases} 1 & if \ k = \arg \ min_a \|X_n - C_a\|^2, a = 1, \ldots k \\ 0 & otherwise \end{cases}$$

$$c_k = \frac{1}{N_k} \sum_{x \in c_k} X$$

Here, $\|.\|$ Measure the distance from the center. The center and number of dots in the C_k group are represented by the c_k and N_k, variables, respectively.

B. Fuzzy C-Means Algorithm

The Fuzzy C-means clustering (FCM), introduced by Bezdek, is an improvement of previous clustering methods [7]. It is based on the minimization of an objective function with respect to the membership of fuzzy **U** and centroids of clusters **V**:

$$J_m(U, V) = \sum_{j=1}^{N} \sum_{i=1}^{C} u_{ij}^m d^2(x_j, v_i)$$

In $X = \{x_1, x_2, \ldots, x_j, \ldots x_N\}$ is a P × N data structure, where P represents the dimension of each of the 'characteristic' vectors x_j vectors and N represents the number of Vector image function. C is the number of clusters. $U_{ij} \subseteq U(P \times N \times C)$ Is the function of the vector xj to the ith gathering, which satisfies $U_{ij} \in [0 \ 1]$ and $\sum_{k=1}^{C} U_{ij} = 1. (j = 1, 2 \ldots \ldots N)$ Beyond what many would consider possible is conceded as:

$$U_{ij} = \sum_{k=1}^{C} \left(\frac{d(x_j, v_i)}{d(x_j, v_k)} \right)^{-\left(\frac{2}{m-1}\right)}$$

V=$\{v_1, v_2, \ldots v_i \ldots v_c\}$ which is a P×C cross section which implies the bundle highlight center takes after:

$$V_i = \frac{\sum_{j=1}^{N}(U_{ij})^m \times j}{\sum_{j=1}^{N}(U_{ij})^m} \ (i = 1, 2, \ldots. C)$$

m ∈ (1 ,α) is a weight exponent in every blurred member that controls the degree of diffusion d2 (x_i, v_i) and is a measure of similarity between x_i and v_i:

$$d^2(x_j, v_i) = \|x_j - v_i\|^2$$

|| . || it can be defined as a direct generalization or Euclidean distance as the distance of Mahalanobis. The X vector feature in the MR image represents the intensity of the pixel P = l. The FCM algorithm optimally optimizes J_m (U, V) with continuous U and V update, for

Until $\left\| U_{ij}^{(l)} - U_{ij}^{(l+1)} \right\| \leq \varepsilon, \varepsilon = \{0 \ to \ 1\}$ where l is the measure of cycles.

III.   PROPOSED ALGORITHM

The algorithm proposed is the integration of k-means and Fuzzy c-means with some modifications. The model is added together with the traditional means k, which is identified by the intensity of the gray level or the intensity of the brain image. In addition to fuzzy c-adhesion media and the Euclidean distance is altered by the characteristics of the image [8]. The k-means based on the model and F-modified by Fuzzy segmentation of the grouping algorithm can write the equation as follows:

$$J = \sum_{i=i+1}^{M} \sum_{j=j+1}^{N} B(x_i, y_j) \times \sum_{i=1}^{K} \sum_{j=1}^{C} P_{ij} \left\| x_i - c_j \right\|^2 \times \sum_{j=1}^{R} \sum_{i=1}^{C} (U_{ij})^m \ d^2(x_j, v_i)$$

Where M and N are the row and column P_{ij}, a binary image matrix. The center of gravity of the group, the number of data points in groups, and the number of groups defined by R, K and C, respectively. The last stroke is defined as blurred c-media whose Euclidean distance depends on the characteristics of the image. The central part is used as a conventional k-means algorithm, defined by the distance from each point to the center of the cluster. Here, B (x_i, y_j) is the coarse image is marked in describing the desired pattern can be below the equation.

$$B(x_i, y_j) = \sum_{i=i+1}^{M} \sum_{j=j+1}^{N} P(x_i, y_j) \times T_{mn}$$

Organization based window is picked by T_{mn} which is given as:

$$T_{mn} = \sum_{i=1}^{M} \sum_{j=1}^{N} P(x_i, y_j) \oplus \sum_{k=1}^{G} \sum_{l=1}^{S} P(x_k, y_l) \quad k \in M, 1 \in N$$

In this equation, there is an image matrix based on the number of gray intensity temperament number, and the number of squares G, S that is used to detect the nature of P (x_i, y_j).) of the image. Here is the temperament-based convolution matrix and cause the image to get the model of the k-means algorithm image [8].

In the diffused medium U_{ij}^m is the function of belonging to which the Euclidean distance d (x, y) is updated by the value image features F= $\{F_1, F_2, \ldots, F_c\}$, the degree of confusion M, and the center has V= $\{V_1, V_2 \ldots V_i \ldots, V_c\}$ is expressed as:

$$U_{ij} = \left[\sum_{k=1}^{C} \left\{ \frac{d(x_j, v_i)}{d(x_j, v_k)} \right\}^{\frac{2}{m-1}} \right]^{-1}$$

In previous studies, this Euclidean distance is used based on one of the features of such a similarity [18], but in our method it is based on features such as contrast, homogeneity, entropy, etc.

Center groups from which cluster locations are detected and tumor can be defined as:

$$V_i = \frac{\sum_{j=1}^{N} (U_{ij})^m \times j}{\sum_{j=1}^{N} (U_{ij})^m} \quad where, (1 = 1,2, \ldots, C)$$

A. We have Extracted the following Five Characteristics for the Classification Category

1) Energy:

$$F_1 = \sum_{i=1}^{G} \sum_{j=1}^{G} |P(x_i, y_i)|^2$$

2) Here, G is the gray level co-occurrence matrix.

3) Contrast:

$$F_2 = \sum_{n=1}^{G} n^2 \sum_{i=1}^{G} \sum_{j=1}^{G} |P(x_i, y_j)| \ and \ |i - j| = n$$

.

4) Homogeneity:

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$$F_3 = \sum_{i=1}^{G} \sum_{j=1}^{G} \frac{P(x_i, y_j)}{1 + \|i + j\|}$$

5) *Entropy:*

$$F_4 = \sum_{i=1}^{G} \sum_{j=1}^{G} P(x_i, y_j)(-\ln(P(x_i, y_j)))$$

6) *Dissimilarity:*

$$F_5 \sum_{i=1}^{G} \sum_{j=1}^{G} P(x_i, y_j)|i - j|$$

B. *Summary of PKFCM Algorithm*
1) Characterize number of dim level and decide square network,
2) $A = \sum \sum P(x_k, y_i)$
3) $P = \sum \sum P(x_i, y_j)$
4) Where A is square network or matrix and P is picture lattice
5) Introduce format of pattern $T_{mn} = P \oplus A$
6) Decide coarse picture, B(xi,yj) from layout, Tmn
7) Reshape format based k-implies portioned picture matrix

$$P_1 = \sum_{i=1}^{K} \sum_{j=1}^{C} P_{ij} \|x_i - c_j\|^2 \times \sum_{i=i+1}^{M} \sum_{j=j+1}^{N} B(x_i, y_j)$$

8)

9) Rehash step 2 to 4 until $T_{mn} \leq \sum_{k=1}^{G} \sum_{i=1}^{i} [T_{mn}(k) - T_{mn}(l)]$
10) Post prepare the P1
11) Decide group centroid, C and level of fluffiness, m.
12) Instate enrollment $U_{ij}^{(0)}$ *of FCM*
13) Compute group focus, $v_i^{(l)} \leftrightarrow U_{ij}^{(l)}, (i = 1,2,\dots C)$ *and* $(l = 0,1,2,\dots)$
14) Decide picture highlights $F(x_j, v_i^{(l)}) \leftrightarrow v_i^{(l)}$
15) Apply adative gamma corections
16) Calculate tumor region using

$$\|U_{ij}^{(l)} - U_{ij}^{(l+1)}\| \leq \varepsilon, \varepsilon = \{0 \text{ to } 1\}$$
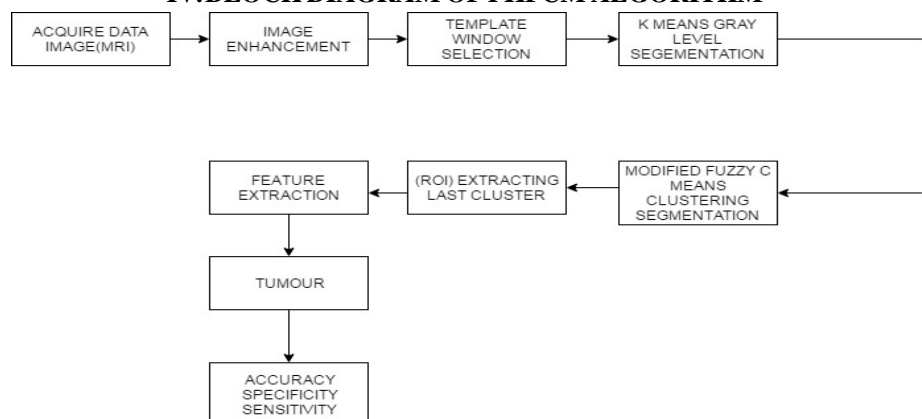
IV. BLOCK DIAGRAM OF PKFCM ALGORITHM

Fig -1: Block diagram of PKFCM

Cerebrum MRI pictures were gathered from various restorative focuses. These cerebrum MRI pictures were changed over into two dimensional lattices utilizing MATLAB (R2015b).This illustration demonstrates a few picture improvement approaches. Three capacities are especially reasonable for differentiation upgrade: imadjust, histeq, and adapthisteq.
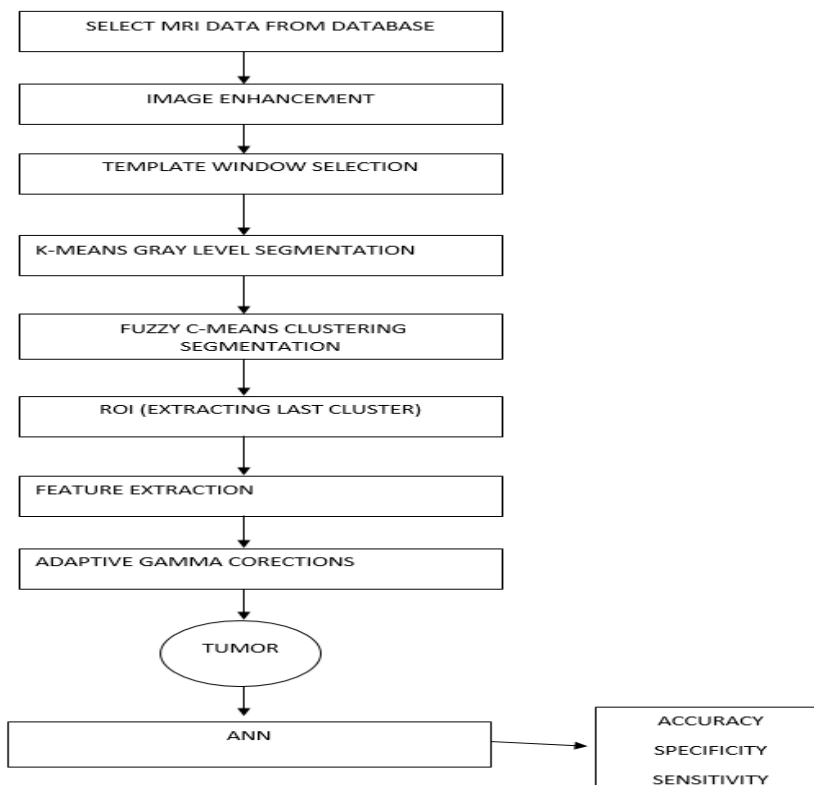
A. *Flow Chart*

Fig -2: Flow chart of PKFCM algorithm

The whole method that has been proposed for the detection of tumor in brain MRI image using pattern based K-means and modified fuzzy C-means is described in the flow chart. In this flow chart firstly there is manipulated acquisition of brain MRI image, and then it is processed and given at the input of pattern based k-means segmentation method. The results from the modified fuzzy C-means with updated membership is obtained, then the extracting the last cluster (ROI) and feature extraction is processed with the adaptive gamma correction, finally the tumor is detected (red line marked) [8].
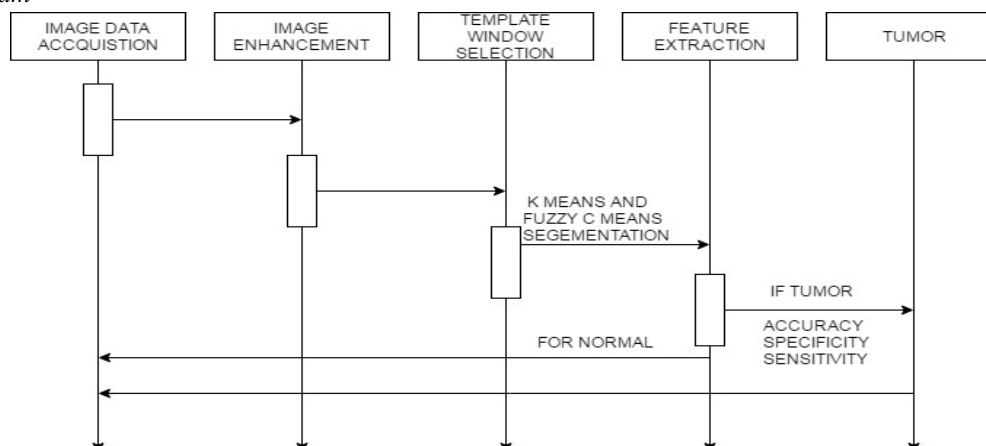
B. *Sequence Diagram*

Fig -3: Sequence diagram of PKFCM algorithm

V. RESULTS AND ANALYSIS

There is a brain tumor image database 30 shown in Figure 5. We arrived at the database through various complex brain tumor images. These images are collected by [6-11] and processed to enhance our algorithm application. Then we processed these images together with Mat lab and obtained the final consumption database shown in Figure 5. The tumor in this image is so critical that it is difficult for common people to identify it so easily. In this algorithm we used PKFCM 3, 5, 10, 27 digital imaging databases to detect the tumor position shown in Figure 6. Hence a small portion of brain tumor not avoided. The input image is first processed through a filter, then in Figure 6 (b) is a first segmentation of images using media patterns k (TK), which is segmented based on the intensity of gray color and temperament. After that, the tumor is detected and reported as a red line in Figure 6 (c) using fuzzy modified c-media (FCM) based on the Euclidean distance from the cluster center for each data point it mainly depends on the different characteristics. This may be important to understand the importance of this modified and embedded method. Based on the intensity of the gray level, the modified FCM is performed for 15 groups. The grouped image is known as an image with smaller gray levels and separates color intensity between them consecutively. For example, multiple images grouped for the incoming image do not. 3 are shown in Figure 7. Here, the tumor portion is selected with another portion of the image shown in a separate image, based on the tumor feature. Here, index no. 13 is automatically selected and marked as a red line in Figure 6. The network-based selection criteria based on the performance of this technique shown in Figure 8. Here the network consists of 30 layers of input vector, a hidden layer neuron 17, and an output layer. Typically, the network consists of three layers such as input layer, hidden layer, and output layer. The input level and output is user-defined, but the hidden layer is selected based on the performance. Hidden layer can be one or more of the analysis, but it is required in the hidden layer n. Layer should be less numbered.
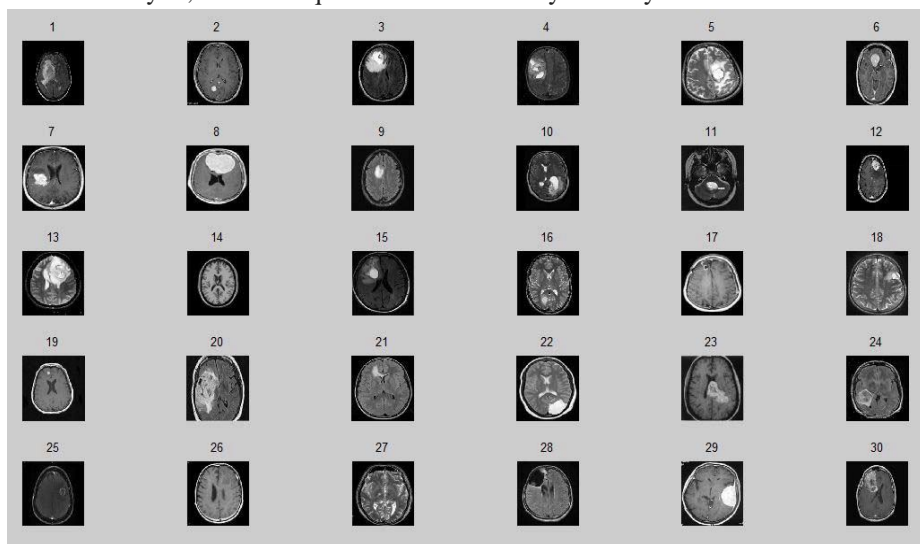

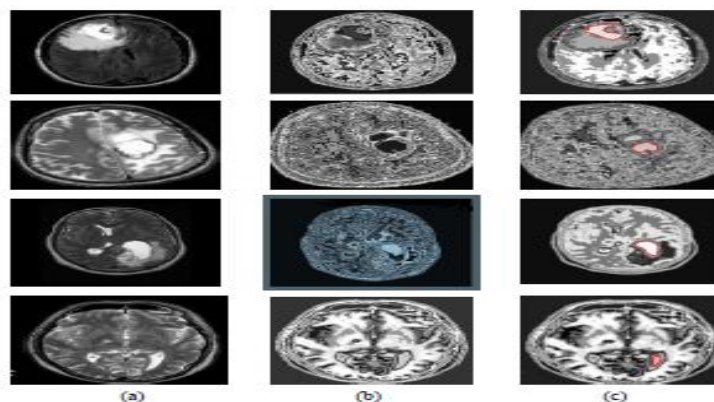Fig -5: The collection of 30 mind tumor MRI picture

Fig -6: (a) Input pictures for PKFCM, (b) Segmented pictures from the first fragmented calculation (TK-implies) with no. of dim level=10, (c) Detected cerebrum tumor pictures from the PKFCM.

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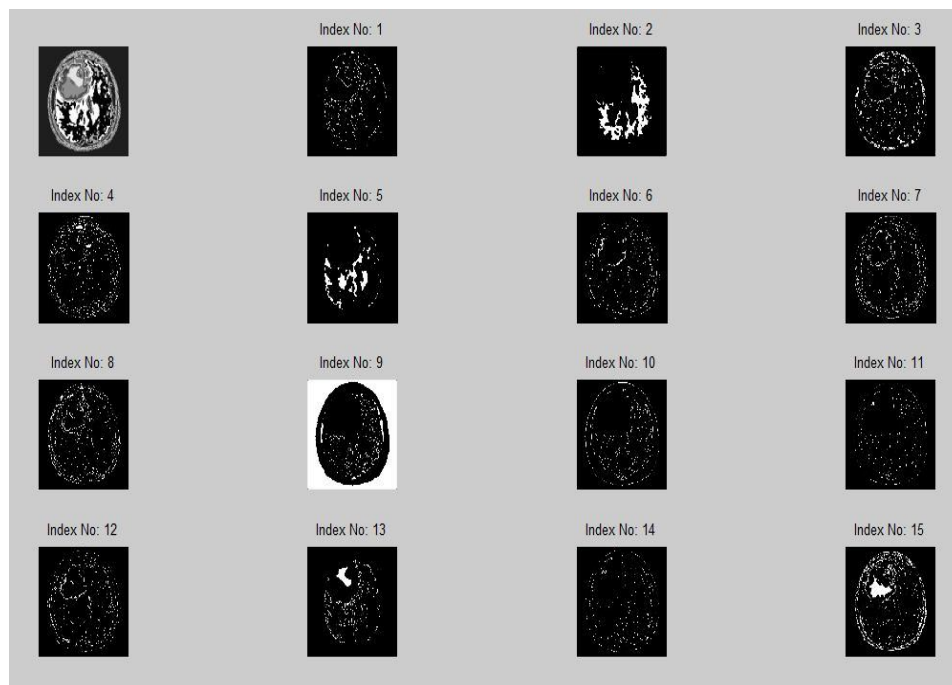
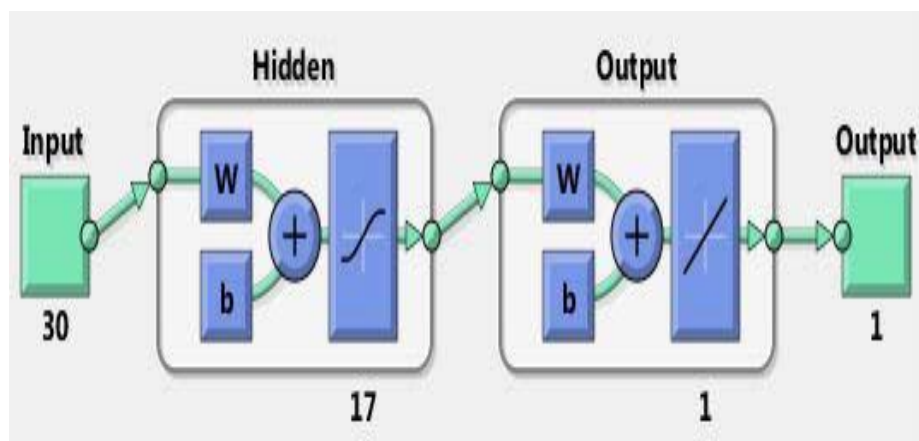Fig -7: Several bunched pictures for information picture

Fig -8: The Neural Network architecture

This method appeared in ANN. Here the structure includes 30 input vector layers, one secured layer with 17 neurons, and one yield layer. Ordinarily the system includes three layers such as information layer, secured layer, and yield layer. The information and yield layer are user defined unlike the camouflaged layer. The number of layers in this hidden layer must be low in number, however the layer itself can be of any number. The execution wind is examined through Fig. 6 of the prepared information, for 60 cycles, augment no. 0.05; execution objective 0.5e-02, least inclination 1e-10, and support check 6. The execution objective is capable between 10 and 12 emphases. Best underwriting execution is 1.5483 at cycle 11. The test information meets close-by underwriting completing it respects. The execution relies on the blunder respect or objective of slightest mistake. In this examination we have utilized bungle respect of0.005 for the movement of our laid out system. It is required that the no. of cycle is minimum and for our structure it has taken 11 emphases to meet the scarcest oversight. This figure shows how the inclination lessening and finished jump a catalyst at 12 emphases. Similarly Levenberg-Marquardt change parameter (MU) increments and decreases at its given respects. Additionally, there are two support check dissatisfaction. The estimation of inclination is come to at 6.6352 for the 12 ages. Again the MU respect is broadened and lessened and then continues to the estimation of 1e-09 at the 12 emphases. Consequently there are 1validation checks at the 12 periods.
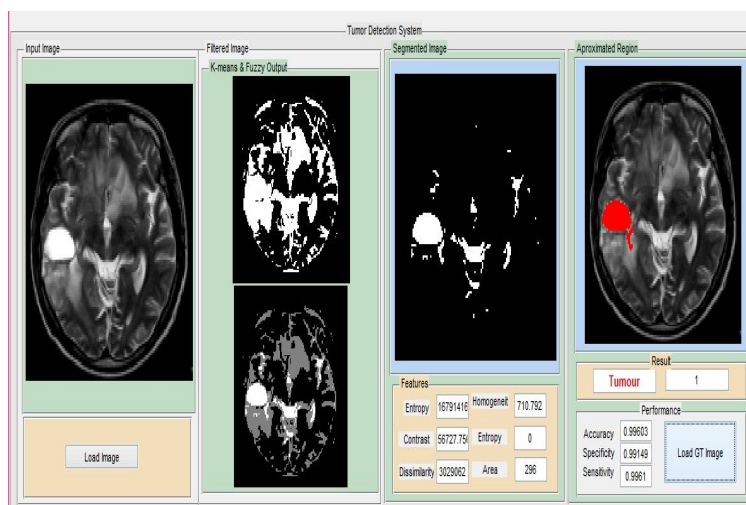
A. *Input MRI Image 1*

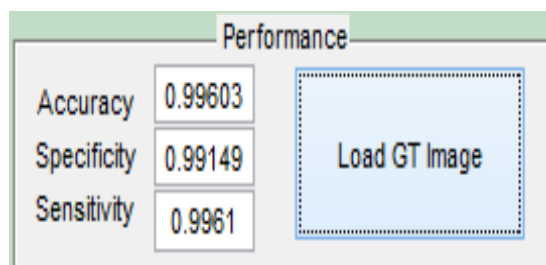Fig -9: Algoritham output for abnormal MRI input image

Fig-10: Result & analysis of abnormal MRI image
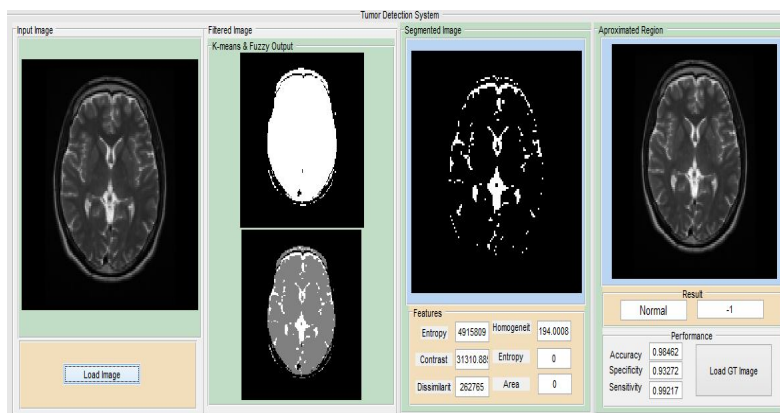
B. *Input MRI Image 2*

Fig-11: Algoritham output for abnormal MRI input image
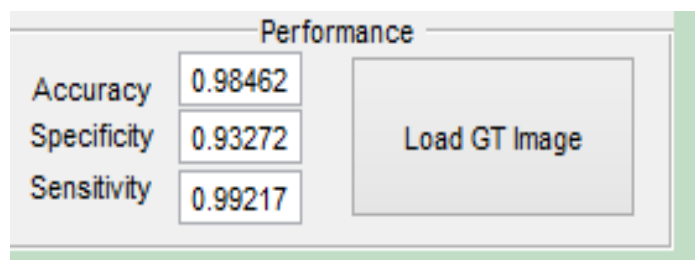

Fig-12: Result & analysis of abnormal MRI image
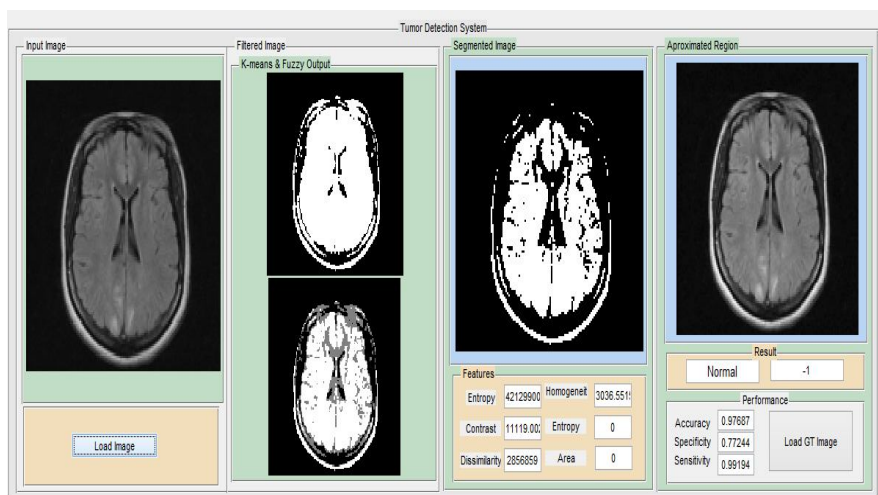
C. Input MRI Image 3

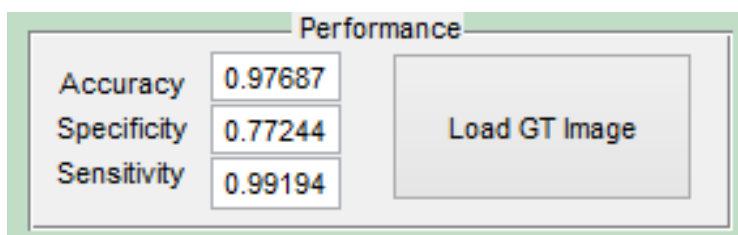Fig -13: Algoritham output for normal MRI input image

Fig-14: Result & analysis of normal MRI image

D. Input MRI Image 4

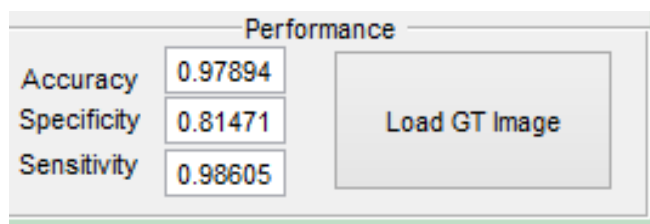Fig -15: Algoritham output for normal MRI input image

Fig-16: Result & analysis of normal MRI image

these are the result which is obtained by using our preposed algoritham.and the performance parameters can be calculated for the 30 brain tumor images through following mathematical expression.

TP=True Positive, TN=True Negative, FP= False Positive, FN= False Negative. These terms are validation metrics used to verify the quality of a segmented image. In a scenario where you want to compare a segmented image with ground truth, taking the image of truth as a comparison basis can assume that the close planes are pixel "white" and "black" pixels are true. The terms which have mentioned is:

True positive (TP): unhealthy people correctly identified as unhealthy (shown in fig-9)

False Positives (FP): healthy people incorrectly identified as unhealthy (shown in fig-15)

True negative (TN): healthy people correctly identified as healthy (shown in fig-13)

False Negatives (FN): unhealthy people incorrectly identified as healthy (shown in fig-11)

In general, Positive = analyzed and negative = discarded. Therefore:

1) True positive = correctly analysed
2) False positive = incorrectly analysed
3) True negative = correctly discarded
4) False negative = incorrectly discarded

Using these constraints the sensitivity, specificity and accuracy is calculated and show.

Sensitivity = TP/ (TP+FN) * 100

Specificty = TN/ (TN+FP) *100

Accuracy = (TP+TN)/ (TP+TN+FN+FP) * 100

Once more, the time required for seeing every tumor picture is 40-50sec, in the Matlab2015b with Core2duo processor.

Table -1: Comparison of existing methods & proposed   PKFCM

Algorithm	Sensitivity (%)	Specificity (%)	Accuracy (%)
FCM	96	93.3	86.6
K-means	80	93.12	93.28
Proposed PKFCM	99.61	99.14	99.60

VI.   CONCLUSIONS

In this project, we proposed a new approach, that is, based on the modified model K-means and Fuzzy C-means algorithm. It is used to eliminate the limitation of the K-means algorithm and FCM for a conventional MRI conventional brain tumor image. The model is selected based on the convolution of the gray level intensity in a small portion of the brain image and the brain tumor. The algorithm is K-means initial voltage through an appropriate selection of the segmentation model. Current adhesion is obtained by measuring the distance from the center of gravity to the groups until it reaches its maximum. Based on the cluster membership up to date and automatically selected, acute segmented image with modified FCM tumor technique is obtained. The segmented tumor is shown as red marked with its detected position. The yield is analyzed by neural networks, which shows greater precision and fewer errors. The precision, sensitivity and specificity of the show that is better than the traditional methods. Although less sensitive to noise, but for some images where the difference in gray level intensity is very small cause problems to select the perfect model.

VII.   ACKNOWLEDGMENT

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