*International Journal of Engineering &Technology*, 8 (4) (2019) 490-499

**International Journal of Engineering & Technology**

*Website: www.sciencepubco.com/index.php/IJET*

***Research paper***



# APSO based LLRBFNN model and enhanced fuzzy C means algorithm for brain tumor detection and classification from magnetic resonance image

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**Abstract**

This paper presents a novel APSO (Accelerated Particle Swarm Optimization) Predicated LLRBFNN (Local Linear Radial Basis Function Neural Network) model for automatic encephalon tumor detection and classification. The enhanced fuzzy c means algorithm (EnFCM) has been proposed for image segmentation and the GLCM (Gray Level Co-occurrence Matrix) technique for feature extraction from MR (Magnetic Resonance) images. This research work aims to utilize the hybrid models and algorithms for relegation and segmentation of encephalon tumors from the MR images. The extracted features have been alimented as input to the proposed APSO predicated LLRBFNN model for relegation of benign and malignant tumors. In this research work the proposed LLRBFNN model weights are optimized by utilizing APSO training which will provide unique solution to mitigation the hectic task of radiologist from manual detection of encephalon tumors from MR Images. Additionally the centers of the LLRBFNN model are culled by the Enhanced Fuzzy C Means algorithm and updated by the APSO algorithm. The results of proposed PSO predicated LLRBFNN model has been compared with PSO-LLRBFNN model, APSO-RBFNN and PSO-RBFNN model and the comparison results are presented. The experimental results obtained from the proposed model shows better relegation results as compared to the subsisting models proposed anteriorly.

***Keywords***: *APSO (Accelerated Particle Swarm Optimization); Enhanced Fuzzy C Means (EnFCM); Fuzzy C Means Algorithm (FCM); LLRBFNN (Local Linear Radial Basis Function Neural Network); PSO (Particle Swarm Optimization); RBFNN (Radial Basis Function Neural Network).*

## 1. Introduction

The manual analysis of tumor predicated on visual interpretation by radiologist may lead to erroneous diagnosis when the number of images increases. To eschew the human error, an automatic system is needed for analysis and relegation of medical images. Segmentation of medical images plays a consequential role in diagnosis and therapy of diseases. It can provide quantitative pathological information about diseases and avail medicos to make decisions. Due to the inefficiency variability residing in manual segmentation, precise and robust automatic segmentation is highly desired. An overview and findings of some of the recent and prominent researches are presented here. The Fuzzy C-Mean (FCM) is one of the most used methods for image segmentation and when compared with hard segmentation methods [2], FCM is able to retain more information from the pristine image. One of the disadvantage of standard FCM is not to consider any spatial information in image, which makes it very sensitive to noise and other imaging artifacts. Ahmed et al. [3] modified the objective function of FCM to compensate for the gray (intensity) inhomogeneity and to sanction the labelling of a pixel to be influenced by the labels in its immediate neighborhood, and they call the algorithm as FCM_S. One disadvantage of FCM_S is that it computes the neighborhood term in each iteration step, which is very time-consuming. In order to reduce the computational loads of FCM_S, L. Szilágyi et al. [4] proposed EnFCM algorithm to expedite the image segmentation process. EnFCM is predicated on a simple fact that, the number of gray levels $q$ is generally much more minuscule than the size N of the image. By utilizing this fact, the time involution of EnFCM can be drastically reduced. However, EnFCM still shares a mundane crucial parameter α with FCM_S and its two variants. The parameter α is utilized to control the trade-off between the pristine image and its corresponding mean- or median-filtered image[5].Using Enhanced FCM, the segmenting time will be reduced compared with the standard FCM. At the same time the classification of tumor tissues equally important for the radiologist.

The research work follows the steps such as (i) MR images has been first segmented by the Enhanced Fuzzy C Means algorithm and the features has been extracted from the images utilizing GLCM (Gray Level Co-occurrence Matrix) feature extraction technique. Further in the second phase (ii) the extracted features has been given as input to the proposed APSO predicated LLRBFNN model for the relegation of encephalon tumors. In the third stage (iii) the centers are culled by Enhanced Fuzzy c betokens algorithm and at the last stage (iv) the centers and the weights are updated utilizing APSO algorithm. The relegation results of malignant and benign tumor from the proposed

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APSO predicated LLRBFNN model has been compared with RBFN predicated PSO model and PSO Predicated LLRBFNN model for the relegation precision. Our results lead to conclude that the proposed APSO predicated LLRBFNN model is congruous to relegate and detect encephalon tumor and integrate clinical decision support systems for the first stage screening and diagnosis by the radiologists or clinical experts.
The rest of this paper is organized as follows. In Section-2, related work by previous researcher has been mentioned and in Section-3 existing Fuzzy C-Means clustering algorithms are presented followed by the EnFCM algorithm. Further in Section-4, the methodology and proposed APSO-LLRBFNN model has been presented, Section-5 presents the experimental comparisons results and Section-6 presents conclusion followed by reference.

## 2. Related work

Chen, X. et al. [6] introduced a super pixel-predicated framework for automated encephalon tumor segmentation for MR images. In this method super pixels belonging to concrete tumor regions are identified by approximation errors given by kernel dictionaries modeling different encephalon tumor structures. Khaled Abd-Ellah, M. et al. [7] segmented MR images utilizing K-betokens clustering then relegated mundane and anomalous tumors utilizing SVM with features extracted via wavelet transform as input. Verma, A. K. et al.[10] decomposed corrupted images utilizing symlet wavelet then proposed a denoising algorithm utilizes the alexander fractional integral filter. Kimia Rezaei and Hamed Agahi [11] presented Support Vector Machine (SVM) with kernel function to segment the tumor region by detecting tumor and non-tumor areas. Chaddad [12] has utilized Gaussian amalgamation model (GMM) for feature extraction and PCA for the enhancement of the GMM feature extraction process. Chen and Zhang [15] proposed two variants, FCM_S1 and FCM_S2, which simplified the neighbourhood term of the objective function of FCM_S by considering mean-filtered image and median-filtered image. Thus the execution times of both FCM_S1 and FCM_S2 are considerably reduced. Cui et al. [17] applied a localized fuzzy clustering with spatial information to compose an objective of medical image segmentation and inequitableness field estimation for encephalon MR images. Nilesh Bhaskarrao Bahadure et al [18] has presented dice kindred attribute index, which is one of the paramount parameters to judge the precision of any encephalon tumor segmentation and support vector machine for relegation. P. K. Nayak and S. Mishra [19], have presented a LLRBFNN model and a modified teaching–learning-predicated optimization for classification of multiple power signal perturbances from which the proposed model has been inspired to relegate the encephalon tumor. Several techniques have been proposed for relegation of encephalon tumors in MR images, such as fuzzy clustering betokens (FCM), support vector machine (SVM), artificial neural network (ANN), erudition-predicated techniques, LLRBFNN predicated PSO and prospect-maximization (EM) algorithm technique which are some of the popular techniques utilized for region predicated segmentation and so to extract the paramount information from the medical imaging modalities. But detection and classification of tumor takes more computational time with the mentioned classifiers. This motivates us to propose APSO based LLRBFNN classifier to reduce computational time to classify tumor tissues from MR images. In this research work, we have employed the enhanced fuzzy c means (EnFCM) algorithms for expeditious and robust image segmentation and culling the center of the Proposed APSO predicated LLRBFNN model.

## 3. Fuzzy C means clustering algorithms

### 3.1. Fuzzy C means algorithm

Let $X = \{x_1, x_2, x_3 ..... x_N\}$ denotes the data with N data samples. Fuzzy C Means [21]-[24] method is based on minimization of the following objective function:

$$J_m = \sum_{k=1}^{N} \sum_{i=1}^{C} u_{ik}^m \left\| x_k - v_i \right\|^2 \tag{1}$$

Where m=2, fuzziness coefficient, $u_{ik}$ is the degree of membership of $x_k$ in cluster $i$, $x_k$ is the $i_{th}$ of $n$-dimensional measured data, $v_i$ is the $n$-dimensional center of the cluster. $\|.\|$ is a norm metric and 'm' is a constant. The parameter 'm' decides the fuzziness of the consequential partition. By definition, for any k we have $\sum_{i=1}^{c} u_{ik} = 1$. To minimize the objective function, it is necessary to assign high membership values to those voxels, whose intensities are situated close to the prototype values of their particular clusters [30].
By taking the derivative of the equation and make it equal to zero by using Lagrange method, the following equations are achieved

$$u_{ik} = \sum_{k=1}^{C} \left[ \frac{\left\| x_k - v_i \right\|}{\left\| x_k - v_k \right\|} \right]^{-2/m-1} \qquad v_i = \frac{\sum_{k=1}^{N} u_{ik}^m . x_i}{\sum_{k=1}^{N} u_{ik}^m} \tag{2}$$

Many variations to the FCM have been proposed because conventional FCM couldn't perform well in the presence of noise and intensity inhomogeneity.

### 3.2. Fuzzy clustering with spatial constraints (FCM_S) and its variants

Ahmed et al. [22] proposed a modification to the standard FCM, in that the neighbourhood effect acts as a regularizer and the modified objective function of FCM_S is defined as follows:

$$J_m = \sum_{i=1}^{c} \sum_{k=1}^{N} u_{ik}^m \left\| x_k - v_i \right\|^2 + \frac{\alpha}{N_R} \sum_{i=1}^{c} \sum_{k=1}^{N} u_{ik}^m \sum_{r \in N_k} \left\| x_r - v_i \right\|^2 \tag{3}$$

Where $x_k$ is the gray value of the k[th] pixel, $v_i$ represents the prototype value of the i[th] cluster, $u_{ik}$ represents the fuzzy membership of the kth pixel with respect to cluster i, $N_R$ is its cardinality, $x_r$ represents the neighbour of $x_k$ and $N_k$ stands for the set of neighbours falling into a window around $x_k$. By definition, each sample point $x_k$ satisfies the constraint that $\sum_{i=1}^{c} u_{ik} = 1$. Two necessary but not sufficient conditions for $J_m$ to be at its local extreme will be obtained as follows:

$$u_{ik} = \frac{\left( \left\| x_k - v_i \right\|^2 + \frac{\alpha}{N_R} \sum_{r \in N_k} \left\| x_k - v_i \right\|^2 \right)^{-\frac{1}{m-1}}}{\sum_{i=1}^{c} \left( \left\| x_k - v_i \right\|^2 + \frac{\alpha}{N_R} \sum_{r \in N_k} \left\| x_k - v_i \right\|^2 \right)^{-\frac{1}{m-1}}} \tag{4}$$

$$v_i = \frac{\sum_{k=1}^{N} u_{ik}^m \left( x_k + \frac{\alpha}{N_R} \sum_{r \in N_k} x_r \right)}{(1+\alpha) \sum_{k=1}^{N} u_{ik}^m} \tag{5}$$

The second term $\sum_{r \in N_k} x_r \Big/ N_R$ in the numerator of (5) is in fact a neighbour average gray value around. In order to reduce the computation, Chen and Zhang [48] proposed a variant of FCM_S, FCM_S1, which simplified the neighbourhood term of FCM_S. And the low-complexity objective function can be written as follows:

$$J_m = \sum_{i=1}^{c} \sum_{k \in N_k} u_{ik}^m \left\| x_k - v_i \right\|^2 + \alpha \sum_{i=1}^{c} \sum_{k=1}^{N} u_{ik}^m \sum_{k \in N_k} \left\| \overline{x_k} - v_i \right\|^2 \tag{6}$$

Where $\overline{x_k}$ is a means of neighbouring pixels lying within a window around $x_k$. An iterative algorithm for minimizing (6) with respect to $u_{ik}$ and $v_i$ can similarly in FCM_S be derived, as:

$$u_{ik} = \frac{\left( \left\| x_k - v_i \right\|^2 + \alpha \left\| \overline{x_k} - v_i \right\|^2 \right)^{-\frac{1}{m-1}}}{\sum_{i=1}^{c} \left( \left\| x_k - v_i \right\|^2 + \alpha \left\| \overline{x_k} - v_i \right\|^2 \right)^{-\frac{1}{m-1}}} \tag{7}$$

$$v_i = \frac{\sum_{k=1}^{N} u_{ik}^m \left( x_k + \alpha \overline{x_k} \right)}{(1+\alpha) \sum_{k=1}^{N} u_{ik}^m} \tag{8}$$

### 3.3. Enhanced fuzzy C means algorithm

A set of MR brain image slices contains around ten million voxels [24]. The intensity of the voxels is generally encoded with 8 bit resolution, that is, there are only 256 possible levels of intensity for each voxel. To considerably reduce the amount of calculations performed during the segmentation process, the EnFCM algorithm has been proposed to speed up the segmentation process for gray level image.
Step 1:
First we apply a local filtering to each voxel. Let us consider the neighbourhood of the $k$ [th] voxel In order to accelerate FCM_S [23], a linearly-weighted sum image $\xi$ is in advance formed from the original image and its local neighbour average image has been modified in terms of:

$$\xi_k = \frac{1}{\alpha} \left( x_k + \frac{\alpha}{N_R} \sum_{j \in N_k} x_j \right) \tag{9}$$

Where $\xi_k$ denote the gray value of the k[th] pixel of the image $\xi$, $x_j$ represents the neighbours of $x_k$, $N_k$ stands for the set of neighbours falling into a window around $x_k$.
Step 2:

Let $q$ denote the number of the intensity levels of the given image which is generally much smaller than N. Denoting $\gamma_l$ is the number of the pixels from the whole stack of slice having the gray intensity value equal to $l$, where $l = 1,2,....q$. Naturally, by definition we have

$$\sum_{i=1}^{q} \gamma_l = N \tag{10}$$

Step-3:
Concretely, the objective function used for fast segmentation the newly-generated filtered image ξ is defined as:

$$J_s = \sum_{i=1}^{c}\sum_{l=1}^{q} \gamma_l u_{il}^m (\xi_l - v_i)^2 \tag{11}$$

Where $v_i$ represents the prototype of the $i$ th cluster, $u_{il}$ represents the fuzzy membership of gray value $l$ with respect to cluster $i$. And under the constraint that $\sum_{i=1}^{c} u_{il} = 1$ for any $l$, minimize $J_s$, specifically, taking the first derivatives of $J_s$ with respect to $u_{il}$ and $v_i$, and zeroing them, respectively, two necessary but not sufficient conditions for $J_s$ to be at its local extrema will be obtained as follows.
We need to find those values of the parameters $u_{il}$ and $v_i$, for which this objective function has the minimal value. Let us consider the Lagrange multiplier

$$J_s = \sum_{i=1}^{c}\sum_{l=1}^{q} \left[\gamma_l u_{il}^m (\xi_l - v_i)^2\right] + \lambda_l \left(1 - \sum_{i=1}^{c} u_{il}\right) \tag{12}$$

Where $u_{il}$ represents the fuzzy membership of gray value $l$ with respect to cluster $i$. And $\lambda_l$ is the Langrange multiplier.
Step 4. Taking the derivative of $J_s$ with respect to $u_{il}$, and equating it to 0, we get:

$$\frac{dJ_s}{du_{il}} = m\gamma_l u_{il}^{m-1}(\xi_l - v_i) - \lambda_l = 0$$

Then

$$u_{il} = \left(\frac{\lambda_l}{m\gamma_l}\right)^{\frac{1}{m-1}} (\xi_l - v_i)^{\frac{-2}{m-1}}$$

From $\sum_{j=1}^{c} u_{il} = 1$, for any $jth$ cluster we obtain

$$\lambda_l = m\gamma_l \left[\sum_{j=1}^{c} (\zeta_l - v_j)^{\frac{-2}{m-1}}\right]^{1-m}$$

Then

$$u_{il} = \left[\sum_{j=1}^{c} \left(\frac{\zeta_l - v_i}{\zeta_l - v_j}\right)^{\frac{2}{m-1}}\right]^{-1}$$

Or

$$u_{il} = \frac{(\xi_l - v_i)^{-\frac{2}{m-1}}}{\sum_{j=1}^{c} (\xi_l - v_i)^{-\frac{2}{m-1}}} \tag{13}$$

Step 5: Taking the derivative of $J_s$, with respect to $v_i$, and equating the derivative to 0, we get

$$\frac{dJ_s}{dv_i} = -2\sum_{l=1}^{q} \left(\gamma_l u_{il}^m (\xi_l - v_i)\right) = 0 \text{, so}$$

$$v_i = \left( \sum_{l=1}^{q} \gamma_l u_{il}^m \xi_l \right) \left( \sum_{l=1}^{q} \gamma_l u_{il}^m \right)^{-1}$$

$$v_i = \frac{\sum_{l=1}^{q} \gamma_l u_{il}^m \xi_l}{\sum_{l=1}^{q} \gamma_l u_{il}^m} \tag{14}$$

The enhanced FCM algorithm for MR brain image segmentation can be summarized as follows:

i) Determine the values of $\{\gamma_l\}_{l=1}^{q}$, select initial cluster prototypes $v_i$ .
ii) Update membership function values according to (13).
iii) Compute the new values for cluster prototypes according to (14).
iv) Repeat (ii-(iii) until the Euclidean norm of the change of the prototype vector is smaller than a previously set small positive number $\varepsilon$ . EnFCM provides comparable segmenting quality in considerably fast manner for the MR brain image.

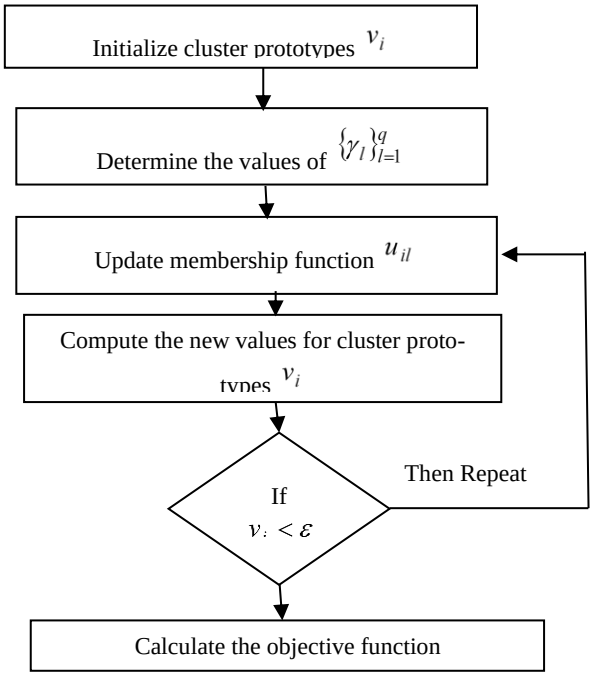



**Fig. 1:** Flow Chart for Enhanced FCM Algorithm.

In this research work, Enhanced Fuzzy c means algorithm has been employed for effective segmentation of brain MR image.

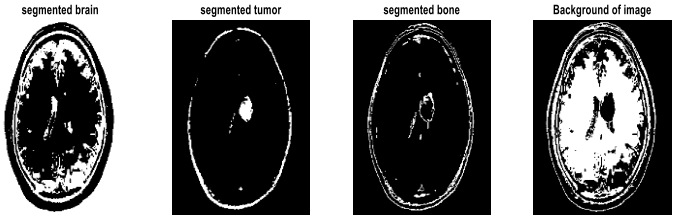



**Fig. 2:** Image Segmentation Using Fuzzy C Means Algorithm.

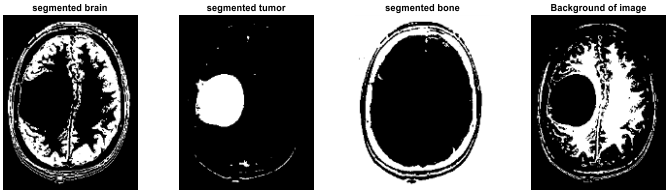



**Fig. 3:** Image Segmentation Using Fuzzy C Means Algorithm with Spatial Constraint.

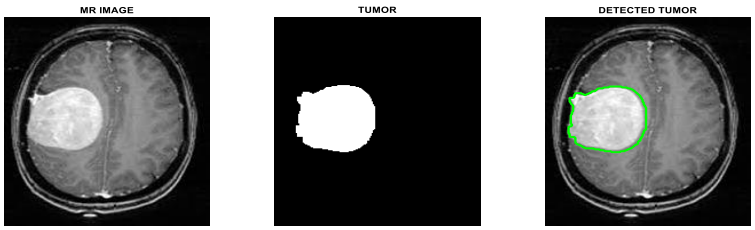



**Fig. 4:** Image Segmentation Using Enhanced Fuzzy C Means Algorithm.

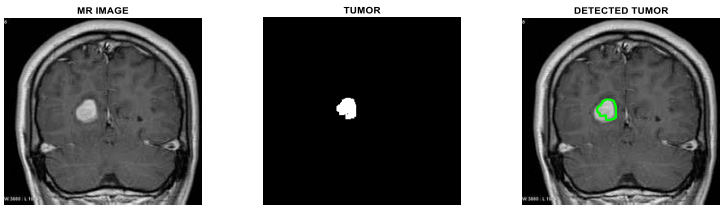



**Fig. 5:** Image Segmentation Using Enhanced Fuzzy C Means Algorithm.

Fig-2 to Fig -5 shows the segmentation results from the MR images. It is found that the Enhanced fuzzy c means provides better visual segmentation results than the other algorithms.

# 4. Methodology

## 4.1. Research work block diagram

The research work is focusing on the classification of brain tumor through clustering algorithms. The work flow accomplished through the three steps. At the first step the images are segmented by the EnFCM algorithm and the features are extracted by GLCM [25] feature extraction technique. In the second step the features are fed as input to the proposed APSO based LLRBFNN model for classification and error calculation. At the third step, the features are fed as input to the existed PSO-LLRBFNN, APSO-RBFNN, and PSO-RBFNN model for comparison of classification accuracy.

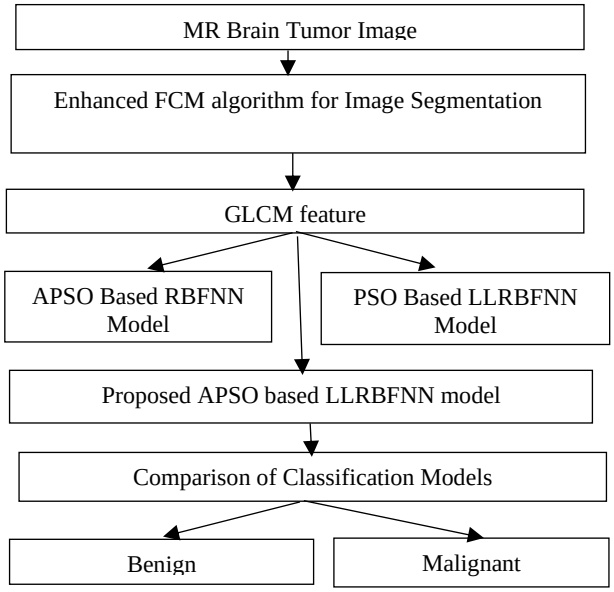



**Fig. 6:** Research Work Flow Block Diagram.

## 4.2. Feature extraction using GLCM (gray level co-occurrence matrix) technique

Feature Extraction is the process of collecting higher level information of an image such as shape, texture, color, and contrast. The features have been extracted by the GLCM feature extraction technique [25] from the image and the normalized feature table is presented. The input MRI images will undergo the process of gray image conversion, computation of correlation undergoes tumor location detection, brain tumor segmentation. A total of seven features such as standard deviation, Mean, Homogeneity, kurtosis, skewness, energy etc, are extracted for classification of benign and malignant tumors using GLCM (Gray Level Co-occurrence Matrix) technique.

**Table 1:** Normalized Feature Extraction

| Images | STD | Mean | Entropy | Homogeneity | Skewness | Kurtosis | Energy |
|---|---|---|---|---|---|---|---|
| Img-1 | 0.1839 | 0.0086 | 0.0711 | 0.3405 | 0.5757 | 0.2406 | 0.0621 |
| Img-2 | 0.1112 | 0.0169 | 0.1235 | 0.2311 | 0.4411 | 0.2194 | 0.1224 |
| Img-3 | 0.1292 | 0.0233 | 0.1593 | 0.2422 | 0.3448 | 0.8614 | 0.1687 |
| Img-4 | 0.1211 | 0.0211 | 0.1416 | 0.3418 | 0.5282 | 0.4641 | 0.1454 |
| Img-5 | 0.1808 | 0.0084 | 0.0701 | 0.2113 | 0.0826 | 0.0704 | 0.0611 |

### 4.3. Proposed APSO based LLRBFNN model

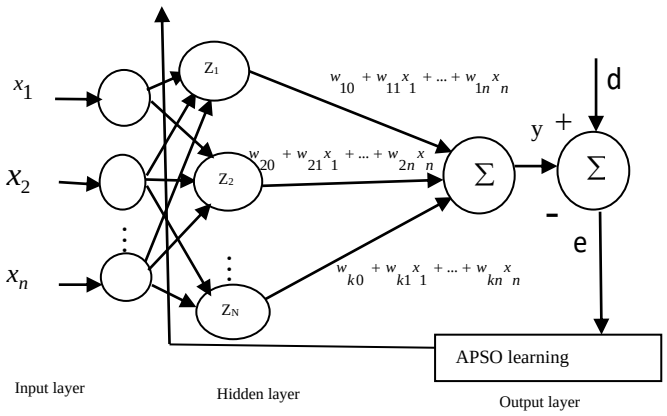



**Fig. 7:** APSO Based Local Linear Radial Basis Function Neural Network.

The weights of the LLRBFNN [16], [19] model replaced by a local linear model between the hidden layer and output layer of conventional RBFNN. In the LLRBFNN model, a random weight is trained iteratively and the local linear weight is given to the hidden node for computation. This reduces the overall nodes required in the network and hence provides better approximation to the pattern classification task. The weights of the LLRBFNN Model is optimised with PSO and APSO algorithm and the results were compared.
In this model the data points $x_1, x_2, ..... x_n$ are inputs (features) and $Z_1$, $Z_2$, -------$Z_N$ are the Gaussian activation function in the hidden units.
The activation function of the n[th] hidden neuron is defined by a Gaussian Kernel as

$$Z_n(x) = e^{\left(\frac{-\|x-v_i(n)\|^2}{2\sigma_n^2}\right)} \tag{14}$$

Where $\sigma_n^2$ is the parameter for controlling the smoothness of the activation function and $C_M$ is the center of the hidden node and $\|x - v_i(n)\|$ indicates the Euclidean distance between the inputs and the function center.
The objective function is to minimize the error and the mean square error is given by

$$MSE(e) = \frac{1}{N}\sum_{n=1}^{N}(d_n - y_n)^2 \tag{15}$$

Where "d" is the desired vector.
In this network the weights are initialized to zero and optimized by using PSO and APSO algorithm.

#### 4.3.1. Weight optimization by PSO

PSO [28, 30] searches the space of an objective function by adjusting the trajectories of individual agents, called particles, as the piecewise paths composed by positional vectors in a quasi-stochastic manner.
Let $x_i$ and $v_i$ be the position vector and velocity for particle i[th], respectively. The new velocity vector is determined by the following formula

$$v_i(t+1) = v_i(t) + \alpha r_1\left[g^* - x_i(t)\right] + \beta r_2\left[x_i^* - x_i(t)\right] \tag{16}$$

Where $r_1$ and $r_2$ are two random vectors, and each entry taking the values between 0 and 1. The parameters α and β are the acceleration constants, say, $\alpha \approx \beta \approx 2$ and $g^*$ is the global best.
There are many variants which extend the standard PSO algorithm, and the most noticeable improvement is probably to use an inertia function $\theta(t)$ so that $v_i(t)$ is replaced by $\theta(t)\ v_i(t)$

$$v_i(t+1) = \theta(t)v_i(t) + \alpha r_1\left[g^* - x_i(t)\right] + \beta r_2\left[x_i^* - x_i(t)\right] \tag{17}$$

Where $\theta \in (0, 1)$ . In the simplest case, the inertia function can be taken as a constant, typically $\theta \approx 0.5 \sim 0.9$.

#### 4.3.2. Weight optimization by APSO

In the accelerated particle swarm optimization (APSO) [27], [28], the velocity vector is generated by a simpler formula

$$v_i(t+1) = v_i(t) + \alpha \in_n + \beta\left[g^* - x_i(t)\right] \tag{18}$$

Where $\in_n$ is drawn from N (0,1) to replace the second term. The update of the position is simply

$$x_i(t+1) = x_i(t+1) + v_i(t+1) \tag{19}$$

In order to increase the convergence even further, we can also write the update of the location in a single step

$$x_i(t+1) = (1-\beta)x_i(t) + \beta g^* + \alpha \in_n \tag{20}$$

It is visually perceived that velocity does not appear in equation (5), and there is no desideratum to deal with initialization of velocity vectors. Comparing with PSO variants, APSO uses only two parameters and a further amendment to the expedited PSO is to reduce the desultoriness as iterations proceed. This denotes that we can utilize a monotonically decrementing function such as

$$\alpha = \alpha_0 e^{-\gamma t} \tag{21}$$

Or $\alpha = \alpha_0 \gamma^t, (0 < \gamma < 1)$ (22)

Where $\alpha_0 \approx 0.5 \sim 1$ is the initial value of the randomness parameter. Here $t$ is the number of iterations or time steps. $0 < \gamma < 1$ is a control parameter [33].
Where t ∈ [0, tmax] and tmax is the maximum of iterations.

#### 4.3.3. APSO process for weight updation

a) Initializing particles (weights of the model) with random position and velocity vectors.
b) Evaluating fitness function for each particle's position using equation (20).
c) If fitness is better than fitness (gbest) then gbest= $g^*$ .
d) Update particles velocity and position equation until convergence obtained.

The parameters are selected for the work for optimisation

a) The Population size taken=50
b) The control parameter α = 0.85t
c) γ =0.75, .β=0.6, $\alpha_0 = 0.65$

#### 4.3.4. Choosing center of the LLRBFNN model using enhanced fuzzy c means algorithm

This process of choosing center is as follows
Step1: Let $X = \{(x_{j1}, x_{j2}, ..., x_{jn})\}$, $j = 1,2,..., N$ is the data set. The centers 'C' have been randomly initialized from the data set.

Step2: Initially take random centers and the data points as the input features.
Step 3: For each data point the center having the maximum probability of finding the nearest mean to each data point, and reassigning the data points to the associated centers, and then re-computing the cluster means is chosen as the corresponding center by using the formula

$$v_i = \frac{\sum_{i=1}^{q} \gamma_i u_{il}^m \xi_i}{\sum_{l=1}^{q} \gamma_l u_{il}^m}$$

The center of the APSO based LLRBFNN model is updated by the formula

$$v_i(n+1) = v_i(n) + \eta(x - v_i(n)) \tag{23}$$

Where $\eta$ =0.8 is the learning parameter
Step 4: Repeat step-2 to step-3 for each data point and the optimized center was obtained at the end of iteration.

## 5. Result and conclusion

The MRI datasets has been collected from the Harvard medical school architecture and Alzheimer's disease Neuroimaging Initiative (ADNI) public database (http://adni.loni.usc.edu/)[35]. A total of 1000 samples have been collected from 100 images. Out of which 75 MR images considered for training and 25 MR images taken for testing. The data is fed as input to the PSO-RBFN, APSO-RBFN, PSO-LLRBFNN and Proposed APSO based LLRBFNN model for error calculation. The proposed model took lesser computational time as compared with the already existed classification models. This proposed model gives classification 98.92% accuracy as we have used Enhanced fuzzy c means algorithm for choosing center and APSO weight updation of the LLRBFNN model.

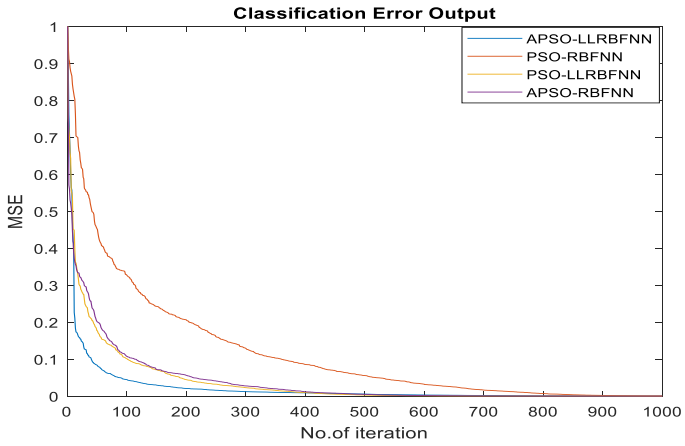



**Fig. 8:** MSE Result Comparison of Algorithms.

**Table 2:** Classification Accuracy Table

| Model | No. of Data | Computational time in seconds | Percentage accuracy |
|---|---|---|---|
| LLRBFNN -PSO | 1000 | 9.213453 | 98.71 |
| LLRBFNN-APSO | 1000 | 12.23421 | 98.92 |
| RBFNN-LMS | 1000 | 22.31613 | 83.51 |
| RBFNN-PSO | 1000 | 18.873592 | 89.22 |
| RBFNN-APSO | 1000 | 16.34527 | 95.23 |

It is found from the Fig.8 that, the proposed APSO based LLRBFNN model takes near about 350 iterations to converge. The PSO-LLRBFNN model takes near about 400 iterations, whereas the PSO-RBFNN and APSO-RBFNN model takes 900 and 550 iterations respectively for the convergence.

## 6. Conclusion

The research work presented a novel APSO based LLRBFNN model for classification and detection of brain tumor images. The features are extracted from MR images using GLCM feature extraction technique and Enhanced FCM applied for image segmentation. The proposed model has shown good potentiality of classifying the tumor into cancerous and non-cancerous. The research work uses Enhanced FCM to choose the centers of the LLRBFNN model and the centers are updated by the APSO algorithm. The proposed LLRBFNN model with APSO and PSO training is the main aim of the paper. The result presented in this paper shows uniqueness of the model and comparison results also shown depicts clear classification accuracies. The results presented from the proposed APSO based LLRBFNN model shows better classification result as compared to the previously used models proposed by the previous researchers. Even though the computational time is slightly more than in the case of proposed model in comparison to the PSO-LLRBFNN model, but the classification accuracy is better in the case of proposed APSO based LLRBFNN model.

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