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Brain tumour Detection and Classification using APSO Based LLWNN Model and Improved Enhanced Fuzzy C Means Algorithm from Magnetic Resonance image

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Abstract: This paper presents a novel APSO Based LLWNN (Local Linear Wavelet Neural Network) model for automatic brain tumordetection and classification.The Improved Enhanced fuzzy c means(IEnFCM) algorithm has been proposed for image segmentation and the GLCM (Gray Level Cooccurrence Matrix) feature extraction technique has been used for feature extraction from MR images.This paper aims to use the hybrid models and algorithms for classification and segmentation of brain tumors from the MR images. The extracted features have been fed as input to the proposed APSO based LLWNN model for classification of Beignin and Malignant tumors. In this research work the proposed LLWNN model weights are optimised by using APSO training which will provide unique solution to relief the hectic task of radiologist from manual detection of brain tumors from MR Images. Also the centersof the LLWNN model are also chosen by the Enhanced Fuzzy C Means algorithm and updated by the APSO algorithm. The results of proposed PSO based LLWNN model has been compared with PSO-LLWNN model, APSO-RBFNN and PSO-RBFNN model and the comparison results also presented in this paper. The experimental results obtained from the proposed model shows better classification results as compared to the existing models proposed.

Keywords: Fuzzy c means algorithm (FCM), Enhanced fuzzy c means(EnFCM), RBFNN,LLWNN(Local Linear Wavelet Neural Network),APSO(Accelerated Particle Swarm Optimization),PSO

I. INTRODUCTION

Automatic encephalon tumor detection becomes an arduous task for the clinical practitioners. Different researchers have been proposed different models for automatic detection and relegation of encephalon tumors and obtained results, which gives somehow relaxation to the radiologists for clinical detection of encephalon tumors from MR images. Medical images mostly contain perplexed structures and their precise segmentation is indispensable for clinical diagnosis. 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. The Fuzzy c-mean (FCM) [2] is one of the most used methods for image , where FCM is able to retain more information from the pristine image. However, one disadvantage of standard FCM is not to consider any spatial information in image context, which makes it very sensitive to noise. Recently, many researchers have incorporated local spatial information into the pristine FCM algorithm to amend the performance of image segmentation [3-6].Ahmed et al. [7] modified the objective function of FCM to compensate for the gray (intensity) inhomogeneity call as FCM_S, but One disadvantage of FCM_S is that it computes the neighbourhood term in each iteration step leads to computational time-consuming.

In order to reduce the computational loads of FCM_S. L. Szilágyi et al. [8] proposed EnFCM algorithm to expedite the image segmentation process. Chen and Zhang [9] proposed two variants, FCM_S1 and FCM_S2, which simplified the neighbourhood term of the objective function of FCM_S. 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. Furthermore, inspired by segmentation as in Enhanced FCM, the segmenting time will be reduced compared with the standard FCM. In this study, we proposed a improved Enhanced FCM(IEnFCM)by introducing a new the fuzzy factor to the EnFCM.

In this research work LLWNN model is considered for classification of brain tumors with APSO training. Our results lead to conclude that the proposed APSO predicated LLWNN model is felicitous 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.In this paper, we propose the Enhanced fuzzy c-means algorithms for expeditious and robust image segmentation and culling the center of the Proposed APSO predicated LLWNN model.

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 using GLCM (Gray Level Cooccurrence Matrix) feature extraction technique . Further in the second phase (ii) the extracted features has been given as input to the proposed APSO based LLWNN model for the classification of brain tumors.
In the third stage(iii) the centers are chosen by Enhanced Fuzzy c means algorithm and at the last stage (iv) the centers and the weights are updated using APSO algorithm . The classification results of malignant and Beignintumor from the proposed APSO based LLWNN model has been compared with RBFN based PSO model and PSO Based LLWNN model for the classification accuracy. It is observed that the result obtained from the proposed APSO based LLWNNmodel shows better classification result as compared to the mentioned algorithms.

The rest of this paper is organized as follows: Section II, presents related work, In Section III, presents the research flow diagram, Improved EnFcm algorithm and proposed APSO-LLWNN model, Section IV, Presents the experimental results and Section V, Presents conclusions followed by reference.

II. Related Work

There are several methods presented for classification and detection of brain tumors. Some of the techniques are presented here as follows: Chen, X. et al. [17] introduced a super pixel-predicated framework for automated encephalon tumor segmentation for MR images. Khaled Abd-Ellah, M. et al. [18] segmented MR images utilizing K-designates clustering then relegated mundane and eccentric tumors utilizing SVM with features extracted via wavelet transform as input. Lang, L. et al. [19] used traditional convolutional neural networks (CNNs) for encephalon tumor segmentation. It automatically learns utilizable features from multi-modality images to coalesce multi-modality information. Kaur, T. et al.[20] proposed an automatic segmentation method on encephalon tumor MR images that performs multilevel image thresholding, utilizing the spatial information encoded in the gray level co-occurrence matrix.

Verma, Kimia rezaei and Hamed agahi [23] presented Support Vector Machine (SVM) with kernel function to segment the tumor region by detecting tumor and non-tumor areas. Torheim et al. [30], and Yao et al.[31]presented a technique which employed texture features, wavelet transform, and SVM’s algorithm for efficacious relegation of dynamic contrast enhanced MR images. Sharma et al.[33] have presented texture-primitive features with artificial neural network (ANN) as segmentation and classifier implement. Wang et al. [35] have presented a medical image segmentation technique predicated on active contour model to deal with the quandary of intensity in homogeneities in image segmentation. Senapati et al[40] proposed breast cancer detection using local linear wavelet neural network and Yuehui Chen et al[55] proposed local linear wavelet neural network for nonlinear function. LLWNN predicated PSO[10] 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. It is observed that from the literature survey that, the models proposed by the researchers previously shows a classification results with different segmentation and classification methods, but not shown the computational time for each techniques, which motivates us to propose a APSO based LLWNN model to have better classification results as well as reduction ion computational time.

III. Methodology

A. Research work flow

The research work is focussing on the relegation of encephalon 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 feature extraction technique. In the second step the features are alimented as input to the proposed APSO predicated LLWNN model for relegation and error calculation. At the third step, the features are alimented as input to the subsisted PSO-LLRBFNN,APSO-RBFNN,PSO-RBFNN model for comparison of relegation precision.

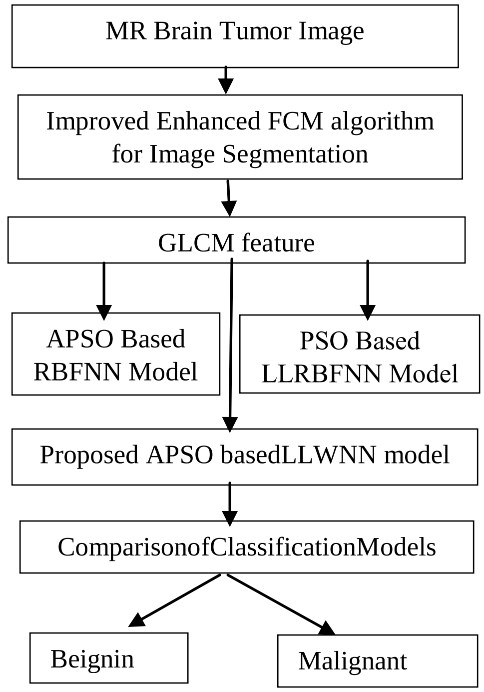

Fig:1 Research work flow block diagram

B. Improved Enhanced Fuzzy C Means Algorithm

Let $X = \{x_1, x_2, x_3 ......x_N\}$ denotes the data with N data samples. It has to be partitioned into c-clusters by minimizing the subsequent cost function

Ahmed et al. [46] proposed a modification to the standard FCM by introducing a termα and the modified objective function of FCM_S is defined as follows:

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

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 $\sum_{i=1}^{c} u_{ik} = 1$.

In order to reduce the computation, Chen and Zhang [48] proposed FCM_S1, which simplified the neighbourhood term of FCM_S. And the low-complexity objective function can be written as follows:

$$J_m = \sum_{i=1}^{c}\sum_{k \in N_k} u_{ik}^m \|x_k - v_i\|^2 + \alpha \sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^m \sum_{k \in N_k} \|\overline{x_k} - v_i\|^2 \quad (2)$$

Where $\overline{x_k}$ is ameans of neighbouring pixels lying within a window around x_k

However, FCM_S1 is unsuitable for the images corrupted by impulse noises [48,49]. In order to overcome that problem,L.Szilágyi et al. [50] proposed the EnFCM(Enhanced fuzzy c means algorithm) algorithm to speed up the segmentation process for gray level image. In order to accelerate FCM_S[49], a linearly-weighted sum image ξ is in advance formed from the original image and its local neighbour average image in terms of:

$$\xi_k = \frac{1}{\alpha}\left(x_k + \frac{\alpha}{N_R}\sum_{j\in N_k} x_j\right) \tag{3}$$

Where ξ_k denote the gray value of the k[th] pixel of the image ξ, x_j represents the neighboursof x_k. Concretely, the objective function used for fast segmenting the newly-generated image ξ is defined as:

$$J_s = \sum_{i=1}^{c}\sum_{l=1}^{q}\gamma_l u_{il}^m (\xi_l - v_i)^2 \tag{4}$$

where q denote the number of the gray levels of the given image which is generally much smaller than N. γ_l is the number of the pixels having the gray value equal to l, and we can write

$$\sum_{i=1}^{q}\gamma_l = N \tag{5}$$

And under the constraint that $\sum_{i=1}^{c} u_{il} = 1$ for any l, minimize 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

$$u_{il} = \frac{(\xi_l - v_i)^{-\frac{2}{m-1}}}{\sum_{j=1}^{c}(\xi_l - v_i)^{-\frac{2}{m-1}}} \tag{6}$$

$$v_i = \frac{\sum_{i=1}^{q}\gamma_l u_{il}^m \xi_l}{\sum_{l=1}^{q}\gamma_l u_{il}^m} \tag{7}$$

The value of α has to be culled immensely colossal enough so that it can eliminate noise, on the other hand, it withal has to be culled diminutive enough so that the after-segmented image does not lose much of its sharpness and details.
Now introducing the fuzzy factor to the cost function to reduce the noise and computational time

$$S_{ti} = \sum_{j\in N_I}\frac{1}{\exp(d_{ij}^2 + 1)}(1 - u_{tj})^m \left\| x_j - v_t \right\| \tag{8}$$

Where d_{ij} is the Euclidean distance between pixel i and j and the u_{ti} is the degree of membership of the j^{th} pixel and v_t is the center of the cluster t

Now the new cost function is given by

$$J_s = \sum_{t=1}^{c}\sum_{l=1}^{q}\gamma_l u_{il}^m (\xi_l - v_t)^2 + \sum_{j\in N_I}\frac{1}{\exp(d_{ij}^2 + 1)}(1 - u_{tj})^m \left\| x_j - v_t \right\| \tag{9}$$

In this research work, improved Enhanced Fuzzy c Means algorithm has been employed for efficacious segmentation of encephalon MR image.

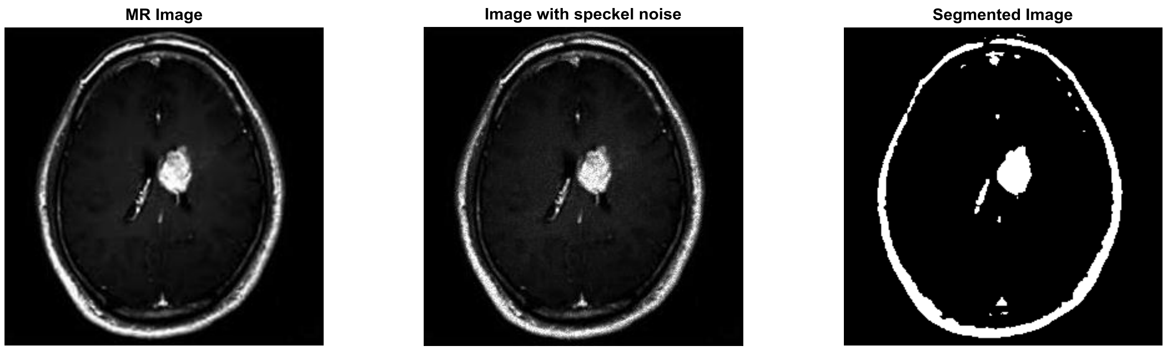

Fig :2Image segmentationusing Enhanced Fuzzy c means algorithm

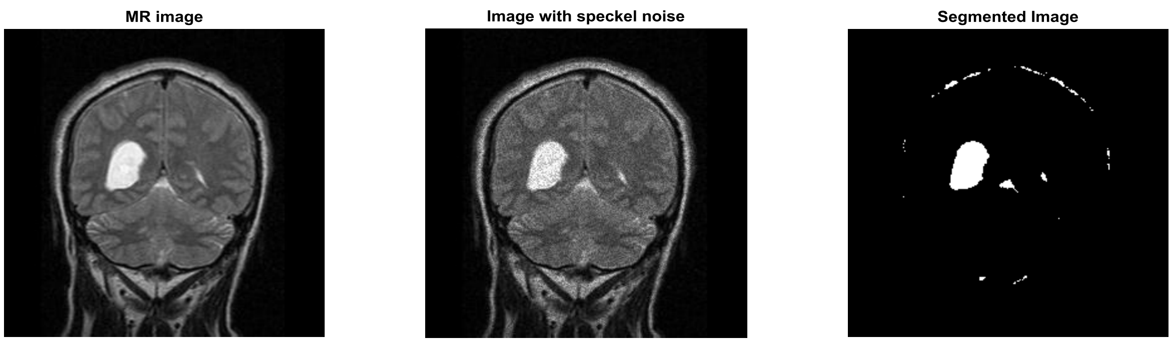

Fig :3Image segmentationusing Improved Enhanced Fuzzy c means algorithm

Table 1: Segmentation Accuracy of Algorithms

Images	FCM	FCM_S	EnFCM	Improved EnFCM
Image 1	87.21	88.34	88.75	96.83
Image 2	88.23	89.56	91.24	97.58
Image 3	85.67	90.25	93.27	97.34
Image 4	87.14	91.45	94.45	98.78
Image 5	87.78	93.43	96.34	98.45
Image 6	88.21	92.57	94.35	98.89
Image 7	89.28	90.21	95.39	98.12
Image 8	88.27	92.34	94.32	98.32
Image 9	87.89	93.49	95.17	98.47
Image 10	88.91	94.56	94.47	98.58

C. Feature extraction using GLCM (Gray Level Co-occurrence Matrix) technique

The features have been extracted by the GLCM feature extraction technique [39,41] from the image and the normalized feature table is presented.

The MRI datasets has been accumulated from the Harvard medical school architecture and Alzheimer's disease Neuroimaging Initiative (ADNI) public database (http://adni.loni.usc.edu/). A total of 100 MR images have been utilized for training and 25 MR images taken for testing. The input MRI images will undergo the process of gray image conversion, computation of correlation undergoes tumor location detection, encephalon tumorsegmentation. A total of seven features are extracted for relegation of benign and malignant tumors utilizing GLCM (Gray Level Cooccurrence Matrix) technique.

Table -2 Normalized Feature Extraction Table

Images	Correlation	DM	IDM	Coarseness	Skewness	Kurtosis	Energy

Img-1	0.1469	0.0322	0.2052	0.1031	0.90198	0.84224	0.23358
Img-2	0.0425	0.002	0.0207	0.2201	0.428481	0.13517	0.0144
Img-3	0.0839	0.0086	0.0711	0.3425	0.575785	0.24065	0.06213
Img-4	0.1112	0.0169	0.1235	0.2011	0.441104	0.21941	0.12249
Img-5	0.0422	0.0019	0.0203	0.2301	0.344871	0.13663	0.01407
Img-6	0.1292	0.0233	0.1593	0.1322	0.344871	0.86141	0.16879
Img-7	0.1211	0.0211	0.1416	0.3418	0.528288	0.46418	0.14542
Img-8	0.0808	0.0084	0.0701	0.2503	0.082658	0.07041	0.06114
Img-9	0.0724	0.0063	0.0552	0.2602	0.370378	0.11171	0.04585
Img-10	0.0294	0.0009	0.0106	0.1928	0.288209	0.03044	0.00665

D. **Quality measures:**The quality measures considered for the research work as follows:

1.Mean Square Error (MSE):

$$MSE = \frac{1}{M \times N} \sum \sum \left(f(x,y) - f^{R}(x,y) \right)^2 \quad (10)$$

2. Structured Similarity Index (SSIM):

$$SSIM = \left(\frac{\sigma_{xy}}{\sigma_x \sigma_y} \right) \left(\frac{2\overline{xy}}{\left(\overline{x}^2\right) + \overline{y}^2 + C_1} \right) \left(\frac{2\sigma_x \sigma_y}{(\sigma_x)^2 + (\sigma_y)^2 + C_2} \right) \quad (11)$$

3.**Peak Signal-to-Noise Ratio (PSNR) in dB.**:

$$PSNR \ in \ \ dB = 20 \log_{10} \left(\frac{2^n - 1}{MSE} \right) \quad (12)$$

4. **Dice Coefficient**:

$$Dice(A,B) = 2 \times \frac{|A_1 \wedge B_1|}{(|A_1| + |B_1|)} \quad (13)$$

Where $A \in (0,1)$ is tumor region extracted from algorithmic predictions and and $B \in (0,1)$ is the experts ground truth.

Table 3: Quality measure analysis for segmented tissues.

Images	MSE	PSNR	SSIM	DICE SCORE
Img-1	1.85	57.34	0.8156	0.87
Img-2	1.89	71.55	0.8832	0.94
Img-3	4.78	68.39	0.9126	0.81
Img-4	2.24	59.45	0.8863	0.80
Img-5	1.34	63.45	0.8634	0.92
Img-6	4.21	60.37	0.8123	0.93
Img-7	4.88	67.48	0.9126	0.91
Img-8	3.24	58.95	0.9263	0.87
Img-9	2.14	64.25	0.8234	0.89
Img-10	3.91	61.27	0.8523	0.90

E. Proposed APSO based LLWNN model

The proposed APSO based LLWNN model is presented in this section for classification. The weights are updated by APSO algorithm.

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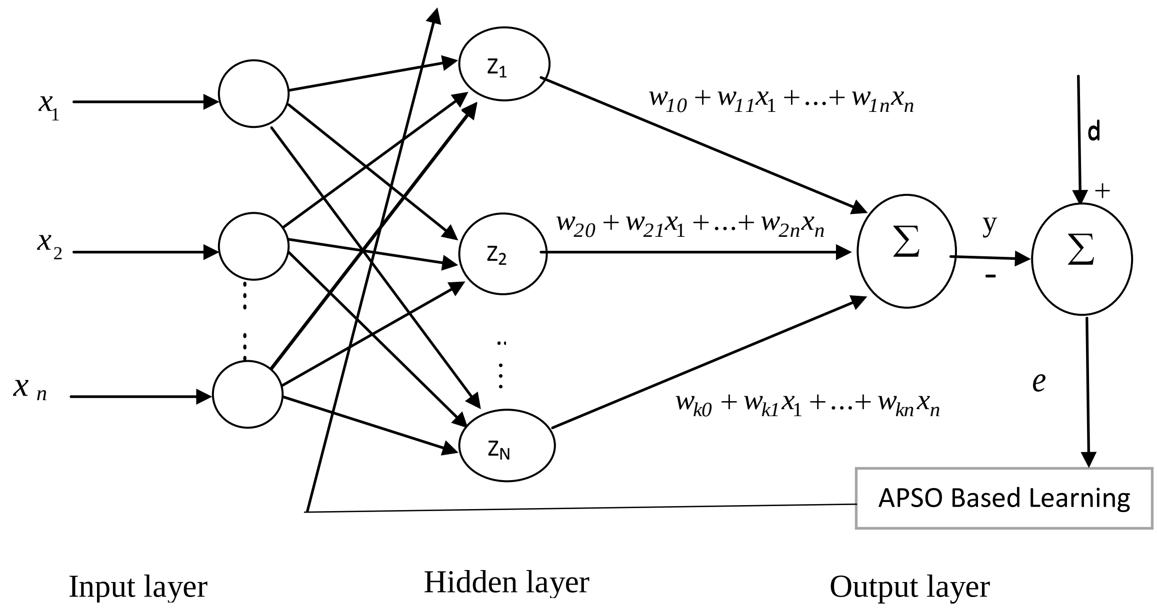

Fig: 4APSO Based Local Linear Wavelet Neural Network

The weights of the LLWNN [40] model replaced by a locallinear model between the hidden layer and output layer of conventional RBFNN. Also. In the LLWNN modelthe input and number of hidden nodes are equalwhich reduces the overall nodes required in the network and hence provides better approximation to the pattern classification task. The weights of the LLWNN Model is optimised with PSO and APSO algorithm and the results were compared.

In this model the data points $x_1, x_2, \ldots\ldots x_n$ are inputs (features) and Z_1, Z_2, -------Z_N are the wavelet activation function in the hidden units.

The activation function of the nth hidden neuron is defined by a wavelet Kernel as

$$Z_n(x) = |a_i|^{\frac{1}{2}} \Psi \left(\frac{x - b_i}{a_i} \right) \tag{14-a}$$

Where the parameters a, b are the scaling and translation parameters, respectively

$$y_n = \sum_{i=1}^{N} \left(w_{i0} + w_{i1}x_1 + \ldots\ldots\ldots\ldots w_{iN}x_N \right) Z_n(x) \tag{14-b}$$

The objective function is to minimize the error and the mean square error is given by

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

Where “d” is the desired vector.

In this network the weights are initialized to zero and optimized by using PSO and APSO algorithm.

F. Weight optimization by PSO

PSO[51,55] has been applied to virtually every area in optimization, computational perspicacity, and design/scheduling applications.

Let x_i and v_i be the position vector and velocity for particle ith , respectively. The new velocity vector is determined by the following formula

$$v_i^{t+1} = v_i^t + \alpha \in_1 \left[g^* - x_i^t\right] + \beta \in_2 \left[x_i^* - x_i^t\right] \qquad (16)$$

where $\in_1$ and $\in_2$ are two random vectors, between 0 and 1. The parameters α and β are the learning parameters or acceleration constants, which can typically be taken as, say, $\alpha \approx \beta \approx 2$.

In 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 $\theta(t)\ v_i^t$

$$v_i^{t+1} = \theta v_i^t + \alpha \in_1 \left[g^* - x_i^t\right] + \beta \in_2 \left[x_i^* - x_i^t\right] \qquad (17)$$

where $\theta \in (0,1)$.

G. Weight optimization by APSO

In the expedited particle swarm optimization (APSO) [52,53], the velocity vector is engendered by a simpler formula

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

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

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

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

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

Typically, α = 0.1∼ 0.5 while β = 0.1 ∼ 0.7 is taken for most of the research work. To reduce the randomness ,a further improvement to the accelerated PSO is is done by using a monotonically decreasing function such as

$$\alpha = \alpha_0 e^{-\gamma t} \qquad (21)$$

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

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 [53].

Where t∈ [0,tmax] and tmax is the maximum of iterations.

The APSO Process for weight follows as:

a. Initializing particles (weights of the model) with random position and velocity vectors.
b. Evaluating fitnessfunction 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,. $\alpha_0 = 0.65$

H. Choosing thecenter of the LLWNN model using Enhanced fuzzy c means algorithm

This process of choosing center is as follows

Step1: Let $X = \left[(x_{j1}, x_{j2}, \ldots, x_{jn})\right], \quad j = 1,2,\ldots,N$ is the data set. The centers 'C' have been randomly initialized from the data set.

Step2: Initially take random centersand 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 recomputing the cluster means is chosen as the corresponding center by using the formula

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

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

$$v_i(n+1) = v_i(n) + \eta(x - v_i(n)) \qquad (23)$$

where η =0.8

Step 4: Repeat step-2 to step-3 for each data point and the optimized center was obtained at the end of iteration.

IV. Result and conclusion

The data taken as 700 which depicts seven features with 100 images ,so a total of 7x100=700 feature data points fed as input to the PSO-RBFN,APSO-RBFN,PSO-LLWNN and Proposed APSO based LLWNN model for error calculation. The experiments are carried out with the software MATLAB2017a. The proposed model is the presented in this paper took lesser computational time as compared with the already existed classification models. This proposed APSO-LLWNN model gives classification accuracy 99.12% accuracy without noiseand 98.28% with noise which shows the robustness of the proposed model.

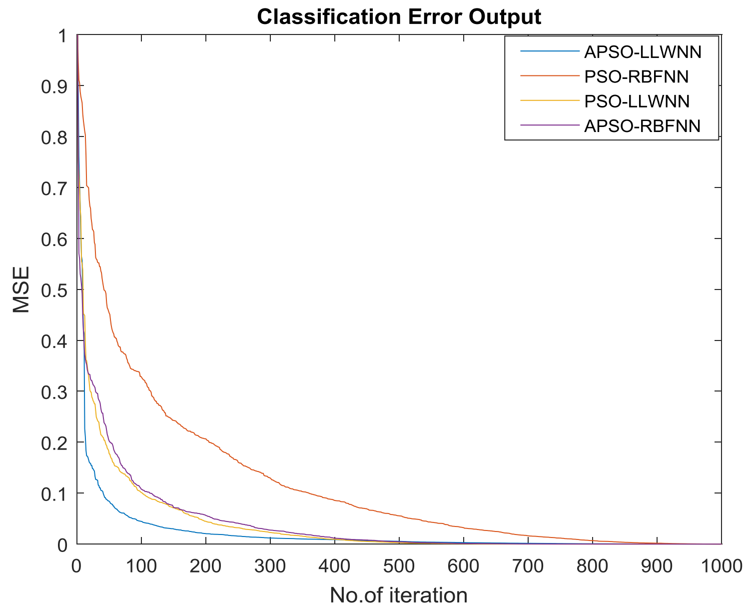

Fig 5: MSE result of proposed APSO-LLWNN model

It is found from the Fig -5 that, the proposed APSO based LLWNN 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 for the convergence. It is evident that the proposed model shows better classification results than the other models presented in Table-2.

Table 2 Percentage Accuracy table

Model	No. of Data	Computational time in seconds	Percentage accuracy with speckle noise	Percentage accuracy without noise
LLWNN -PSO	700	9.213453	98.71	98.91
LLWNN-APSO	700	12.23421	98.28	99.12
RBFNN-LMS	700	22.31613	83.51	92.23
RBFNN-PSO	700	18.873592	89.22	93.35
RBFNN-APSO	700	16.34527	95.23	96.45

V. Conclusion

The research work presented a novel APSO predicated LLWNN model for relegation and detection of encephalon tumor images and Improved Enhanced FCM for image segmentation. The features are extracted from MR images utilizing GLCM feature extraction technique. The proposed model has shown good potentiality of relegating the tumor into cancerous and non-cancerous. The research work uses Improved Enhanced FCM to choose the centers of the LLWNN model and the centers are updated by the APSO algorithm. The proposed LLWNN 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 withal shown depicts clear relegation accuracies. There are ten features have been utilized for the purport of relegation task. The results presented from the proposed APSO predicated LLWNN model shows better relegation result as compared to the foretime used models proposed by the antecedent researchers. Albeit the computational time is scarcely more than in the case of proposed model in comparison to the PSO-LLWNN model, but the relegation precision is better in the case of proposed APSO predicated LLWNN model.

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