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Research Article

BRAIN TUMOR CLASSIFICATION USING HYBRID Fuzzy C MEANS BASED RADIAL BASIS FUNCTION NEURAL NETWORK

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ABSTRACT

The manual detection and classification of the tumor becomes a rigorous and hectic task for the radiologists. An automatic detection and classification of brain tumor using a Hybrid Fuzzy C Means based Radial Basis Function Neural Network from the MR images is presented in this paper. The MR images has been first segmented by the K- 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 the extracted features has been aligned as input to the proposed Fuzzy C Means based Radial Basis Function Neural Network for the classification of brain tumors. The weights of the Radial Basis Function Neural Network updated by the PSO (Particle Swarm optimization) algorithm and the centers of the Radial Basis Function Neural Network are chosen by Fuzzy C Means algorithm. Also the malignant and Beignin tumor has been clustered by the Fast Fuzzy C-Means, K-Means, and KNN for visual localization. The performance of the proposed model has been compared with the Fast Fuzzy C-Means, KNN algorithm, Fuzzy c means algorithm. The result obtained from the proposed hybrid algorithm shows better classification result as compared to the previously used conventional algorithms..

INTRODUCTION

The brain tumors are of mainly two types as malignant and Beignin. The brain tumos symptoms caused by brain tumors are such as hypertensions, change in pattern of headaches, that gradually become more frequent and more severe, vomiting,Vision problems, such as blurred vision, double vision or loss of peripheral vision leads to eye ball reverse,paralysing of mouth leads to abnormal talk, Gradual loss of sensation leads to improper walk, Hearing problems etc. are all the symptoms are found one by one when the brain tumor starts growing. There are mainly two categories of brain tumors are ther as per the research in medical study. The Primary brain tumors originate in the brain itself or in tissues close to it, such as in the brain-covering membranes (meninges), cranial nerves, pituitary gland or pineal gland. Primary brain tumors begin when normal cells acquire errors (mutations) in their DNA. These mutations allow cells to grow and divide at increased rates and to continue living when healthy cells would die. The result is a mass of abnormal cells, which forms a tumor. In adults, primary brain tumors are much less common than are secondary brain tumors, in which cancer begins elsewhere and spreads to the brain. As per the MyoclinicGliomas[1] is a type of tumors begin in the brain or spinal cord and include astrocytomas, ependymomas, glioblastomas, oligoastrocytomas and oligodendrogliomas. Meningiomas is a type of tumor that arises from the membranes that surrounds brain and spinal cord (meninges). Most meningiomas are noncancerous. Acoustic neuromas (schwannomas) are benign tumors that develop on the nerves that control balance and hearing leading from your inner ear to your brain. Pituitary adenomas are mostly benign tumors that develop in the pituitary gland at the base of the brain. These tumors can affect the pituitary hormones with effects throughout the body.Medulloblastomas are the most common

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cancerous brain tumors in children. A medulloblastoma starts in the lower back part of the brain and tends to spread through the spinal fluid. These tumors are less common in adults, but they do occur. Also theCraniopharyngiomas [1] are the rare, noncancerous tumors start near the brain's pituitary gland, which secretes hormones that control many body functions. As the craniopharyngioma slowly grows, it can affect the pituitary gland and other structures near the brain. Secondary (metastatic) brain tumors are tumors that result from cancer that starts elsewhere in the body and then spreads (metastasizes) to the brain. According to the medical practitioner, If it is not operated in advance, the chances of survival becomes difficult for a tumor affected patient. The classification and detection of the brain tumor's have been presented by the researchers through different classifiers such as SVM,PNN,RBFNN etc and found classification results in terms of accuracy and computational time for the cancerous and noncancerous brain tumors.

This paper presents a novel Fuzzy C Means based Radial Basis Function Neural Network for classification of the brain tumors. In this work, the weights of the Radial Basis Function Neural Network has been updated by the PSO algorithm and the centers are chosen by the K- Means algorithm. The MR Images are segmented by the K-Means algorithm and features have been extracted through a popular Gray Level Cooccurrence Matrix (GLCM) feature extraction technique and the extracted features are applied to the, proposed Fuzzy C-Means based Radial Basis Function Neural Network model for clustering of brain tumors for visual localization and compared with the conventional KNN, SVM and recently published Fast fuzzy c-means algorithm. It is found that the proposed algorithm outperforms well in comparisons to the existed classifiers.
This paper organizes follows: the Section-2 presents the related work, Section 3 presents the methodology, proposed model with artificial bee algorithm updation, Fast fuzzy c means algorithm, Section 4 presents the results followed by the conclusion and reference.

Related Work

MohdFauzi Bin Othman, NoramalinaBt Abdullah **[2]** in 2011, presented the classification results of brain tumor of 65% using wavelet (Daubechies (db4)) and Support Vector Machine (SVM). MohdFauzi Othman and MohdAriffananMohdBasri, 2011, [3], uses Principal Component Analysis and Probabilistic Neural Network (PNN) and reported precision of 73 to 100% with varying spread values from 1 to 3. Damodharan and Raghavan [4] have presented a precision of 83% utilizing neural network predicated classifier for encephalon tumor detection and relegation. Alfonse and Salem [5] have proposed SVM predicated classifier and expeditious Fourier transform (FFT) technique for automatic relegation of encephalon tumor from MR images and obtained a precision of 98.9%. Kumar and Vijayakumar [6] reported a relegation precision of 94% utilizing principal component analysis (PCA) and SVM and claims The classification accuracy to identify tumor type of this method is 94%.Cui *et al*. [7] proposed a localized fuzzy clustering and used Jaccard similarity index as a measurement of the segmentation accuracyto segment white matter, gray matter, and cerebrospinal fluid with spatial information and claimed precision between 83% to 95% and claim 83% to 95% accuracy. Sharma *et al*. [8] reported a highly efficient method of texture-primitive features with artificial neural network (ANN) as segmentation and classifier tool and claims accuracy of 100% in the classification of brain tumor from MR images. Zanaty [9] presented a methodology for encephalon tumor segmentation predicated on a hybrid type of approach with FCM and obtained precision of 90% at the noise level.

Wang *et al*. [10] have presented a medical image segmentation technique predicated on active contour model to deal with the quandary of intensity in homogeneities in image segmentation. Torheim*et al*. [11], claimed better presages and ameliorated clinical factors, tumor volume, and tumor stage in comparison with first-order statistical features utilizing wavelet transform, and SVM's algorithm. Deepa and Arunadevi [12] have proposed a technique of extreme learning machine for classification of brain tumor from 3D MR images. Chaddad [13] has used Gaussian mixture model (GMM) for feature extraction and PCA for the enhancement of the GMM feature extraction process and obtained an accuracy of 97.05% for the T1-weighted and T2-weighted and 94.11% for FLAIR-weighted MR images. NileshBhaskarraoBahadure*et al* [14] has presented dice similarity index, which is one of the important parameters to judge the accuracy of any brain tumor segmentation and support vector machine for classification and achieved 96.51% accuracy,94.2% specificity, and 97.72% sensitivity.The literature survey shows different classification techniques, segmentation process for brain tumor detection but the clustering classification is yet not considered. In this present work we have presented the novel clustering classification of benign and malignant tumors using proposed K-Means based RBFN algorithm and Fast Fuzzy C Means algorithm.

METHODOLOGY

Research Flow 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 K-Means algorithm and the features are extracted by GLCM feature extraction technique.

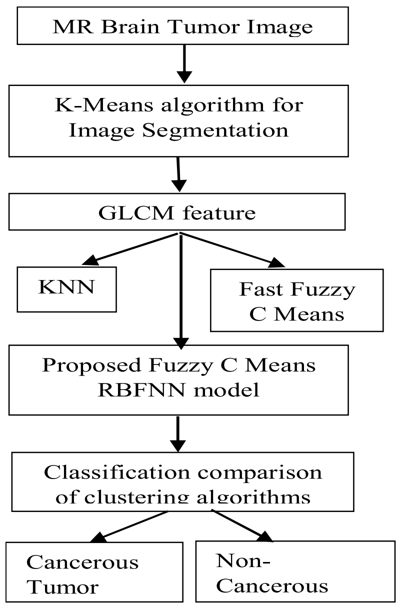

Fig 1 Research Flow Diagram

In the second step the features are fed as input to the proposed Fuzzy C Means RBFNN model for clustering. At the third step, the features are fed as input to the existed KNN, Fast Fuzzy c means clustering algorithm and SVM for the comparison of classification accuracy.

Feature Extraction and Image Segmentation Using K-Means Algorithm

The MRI datasets has been retrieved from the Harvard medical school architecture and Alzheimer's disease Neuroimaging Initiative (ADNI) public database (http://adni.loni.usc.edu/) and Harvard medical center. A total of 200 MR images of normal and abnormal images have been employed for training, testing and clustering classification by the proposed model. The input MR images will undergo the process of gray image conversion, K-Means algorithm for tumor location detection, brain tumor segmentation.

The features have been extracted by the GLCM feature extraction technique [16]from the image and the normalized feature table is presented. It is found that the features Variance versus kurtosis, skewness and energy are providing distinctive values for classification of benign and malignant tumors. The features are given as input to the proposed Hybrid RBFNN algorithm for classification. Also the features are fed as input to the Fast Fuzzy C Means, KNN and Fuzzy C Means algorithm for the classification comparison of benign and malignant tumors.Fig-2 to Fig-4 shows the segmentation process achieved by K-Means algorithm. It found that the segmentation process clearly indicates the segmented tumor, segmented brain, bone and background image.

Table 1 Normalized Feature Extraction Table

Images	Std.Dev	Mean	Entropy	Variance	Skewness	Kurtosis	Energy
Img-1	0.0674	0.0056	0.0502	0.0001	0.433553	0.21473	0.04087
Img-2	0.1662	0.0448	0.2638	0.0046	0.859783	0.55366	0.32506
Img-3	0.1812	0.0599	0.3127	0.0059	0.565063	0.32322	0.43471
Img-4	0.1812	0.0599	0.3271	0.0059	0.565063	0.32322	0.43471
Img-5	0.1402	0.0294	0.1914	0.0031	0.440845	0.30207	0.21342
Img-6	0.1536	0.0366	0.2266	0.0034	0.754417	0.52534	0.26581
Img-7	0.1617	0.0569	0.3151	0.0031	0.491599	0.34039	0.41322
Img-8	0.1123	0.0178	0.1129	0.0021	0.214918	0.10529	0.12936
Img-9	0.1123	0.0178	0.1229	0.0031	0.214918	0.10588	0.12936
Img-10	0.0611	0.0043	0.0397	0.0002	0.470329	0.15568	0.0309
Img-11	0.1469	0.0322	0.2052	0.0031	0.90198	0.84224	0.23358
Img-12	0.0425	0.002	0.0207	0.0001	0.428481	0.13517	0.0144
Img-13	0.0839	0.0086	0.0711	0.0005	0.575785	0.24065	0.06213
Img-14	0.1112	0.0169	0.1235	0.0011	0.441104	0.21941	0.12249
Img-15	0.0422	0.0019	0.0203	0.0001	0.344871	0.13663	0.01407
Img-16	0.1292	0.0233	0.1593	0.0022	0.344871	0.86141	0.16879
Img-17	0.1211	0.0211	0.1416	0.0018	0.528288	0.46418	0.14542
Img-18	0.0808	0.0084	0.0701	0.0003	0.082658	0.07041	0.06114
Img-19	0.0724	0.0063	0.0552	0.0002	0.370378	0.11171	0.04585
Img-20	0.0294	0.0009	0.0106	0.0028	0.288209	0.03044	0.00665

Fuzzy C Means Algorithm

In Fuzzy C means clustering [21] we determine the cluster center C_i and the membership matrix U and we thus determine distinct clusters. Fuzzy C Means method is based on minimization of the following objective function:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \left\| x_i - c_j \right\|^2 \quad (1)$$

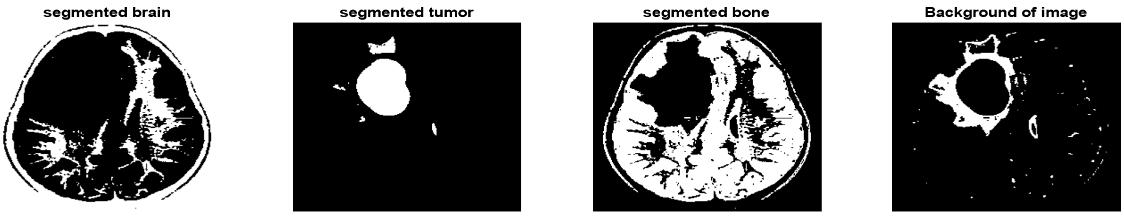

Fig2

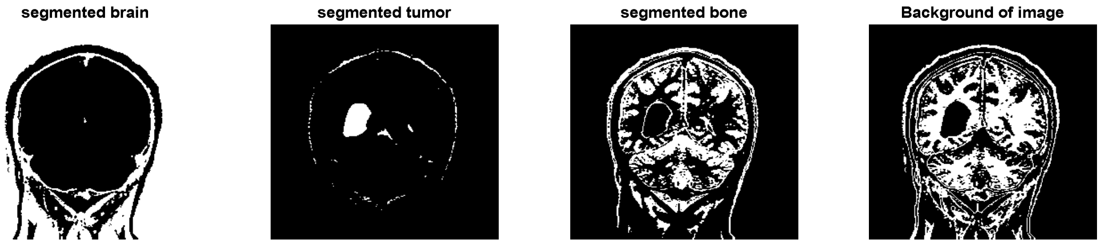

Fig 3

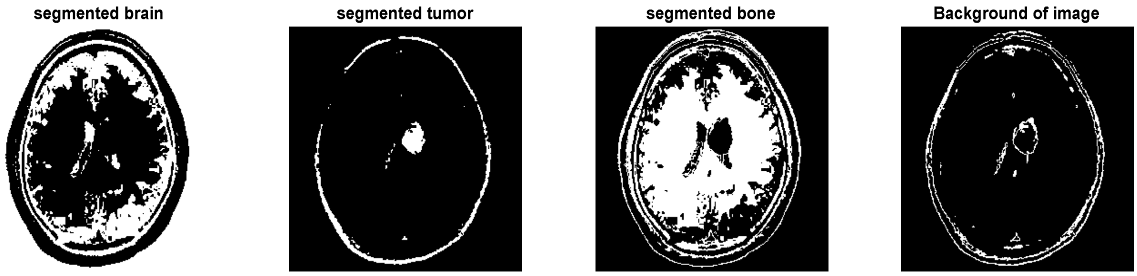

Fig 4

Where m=2, fuzziness coefficient, u_{ij} is the degree of membership of x_i in cluster j, x_i is the i_{th} of n-dimensional measured data, c_j is the n-dimensional center of the cluster.

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m . x_i}{\sum_{i=1}^{N} u_{ij}^m}, u_{ij} = \sum_{k=1}^{C}\left[\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right]^{-2/m-1} \quad (2)$$

Fast Fuzzy C Means Algorithm

According to Fast fuzzy c means algorithm[22] Let $X = [x_1, x_2 ....x_n]$ be a n sample data set and assume that each sample x_k is represented by a set of p features and U is the hard partition matrices whose general term is given by $u_{ik} = 1$ if $x_k \in X_i$, and 0 otherwise. To get partition matrix , the HCM (Hard c Means) algorithm is chosen which minimizes the objective function

$$j = \sum_{k=1}^{n}\sum_{i=1}^{L} u_{ik}^m \|x_k - C_i\|^2 \quad (3)$$

where "L" is the number of clusters and C_i is the cluster center and "m" is the Fuzzifier exponent and $u_{ik} \in [0,1]$.

Minimization of equation (1) is obtained by an optimization technique that successively updates the cluster centers C_i and partition matrix U by using the formula

$$C_i = \frac{\sum_{k=1}^{n} u_{ik}^m x_k}{\sum_{k=1}^{n} u_{ik}^m} \quad (4)$$

$$\text{And } u_{ik} = \frac{1}{\sum_{j=1}^{L} \frac{\|x_k - C_i\|}{\left(\|x_k - C_j\|\right)^{2/(m-1)}}} \quad (5)$$

KNN algorithm

K nearest neighbor (KNN) [20] is a simple algorithm, which stores all cases and classify new cases based on similarity measure. KNN algorithm also called as 1) case based reasoning 2) k nearest neighbor 3)example based reasoning 4) instance based learning 5) memory based reasoning 6) lazy learning.

Typically the object is classified based on the labels of its *k* nearest neighbors by majority vote. If *k*=1, the object is simply classified as the class of the object nearest to it. When there are only two classes, *k* must be a odd integer. After we convert each image to a vector of fixed-length with real numbers, we used the most common distance function for KNN which is Euclidean distance:

$$d(x, y) = \sum_{i}^{k} \sqrt{(x_i - y_i)(x_i - y_i)'}$$ Where x and y are histograms in X.

Proposed K-Means based RBFN algorithm

A RBFNN is an artificial neural network that uses radial basis functions as activation functions. Figure shows the structure of the RBFNN [17]. The RBFNN is three layered feed-forward neural network. The first layer is linear and only distributes the input signal, while the next layer is nonlinear and uses Gaussian functions. The third layer linearly combines the Gaussian outputs. Only the tap weights between the hidden layer and the output layer are modified during training. This algorithm overcomes many issues in traditional gradient algorithms such as stopping criterion, learning rate, number of epochs and local minima. Due to its shorter training time and generalization ability, it is suitable for real-time applications. The radial basis function selected is usually a Gaussian kernel for pattern recognition application. Generally the center and distribution of activation functions should have characteristic similar to data. Here, the center and width of Gaussians are selected using fuzzy c means clustering algorithm. Based on universal approximation theory center and distribution of activation functions are not deterministic if the numbers of hidden neurons being sufficient enough, one can say that the single hidden layer feed-forward network with sufficient number of hidden neurons can approximate any function to any arbitrary level of accuracy.

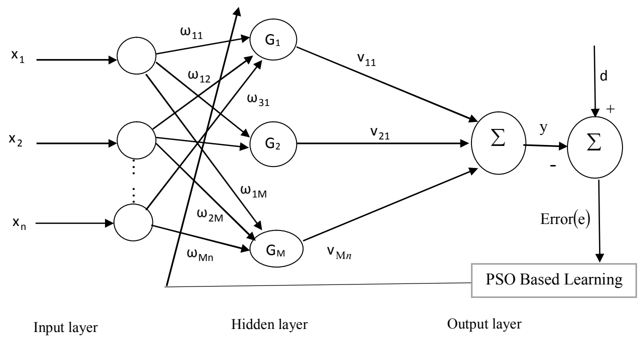

Fig: 5 Fuzzy C Means Based RBFN Network

In this model, it is noticed that in RBFNN [19] model the input and number of hidden nodes are equal. In the RBFNN model, a random weight is trained iteratively and weights has been assigned to the computational hidden node. This reduces the overall nodes requirement and provides better approximation to the pattern classification task.

The activation function of the N^{th} hidden neuron is defined by a Gaussian Kernel as

$$Z_N(x) = e^{\left(\frac{-\|x_i - C_j\|^2}{2\sigma_n^2}\right)} \quad (6)$$

Where σ_n^2 is the parameter for controlling the smoothness of the activation function and C_j is the center of the hidden node and $\|x_i - c_j\|$ indicates the Euclidean distance between the inputs and the function center.

The output at the output layer is given by

$$y = \sum_{n=1}^{N} (v_{11}x_1 + v_{12}x_2 -----v_{Mn}x_n).e^{\left(\frac{-\|(x_N - C_M)\|^2}{2\sigma_M^2}\right)} \quad (7)$$

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

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

Where "d" is the desired vector.

In this network the weights are initialized to zero and optimized by using PSO algorithm [17,18]. In each learning cycle, the input feature vectors are presented in a sequential manner, and the output vector is calculated. The error is calculated by subtracting the actual output from the desired output vector:

PSO is a population based stochastic optimization technique inspired by social behavior of bird flocking. A concept for optimizing nonlinear functions using particle swarm methodology. PSO uses a population of individuals, to search feasible region of the function space. In this case, each solution is called particle and represents a population such as features. The population is set of features and is called as swarm. The particles change their components and fly in a search space.

The velocity update equation is given by

$$v_i(t+1) = wv_i(t) + c_1r_1(pbest(t) - x_i(t)) + c_2r_2(gbest(t) - x_i(t)) \quad (8)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (9)$$

And the position update equation is given by

The PSO Process follows as

1. Initializing particles with random position and velocity vectors.
2. Evaluating fitnessfunction for each particle's position taken as P.
3. If fitness P is better than fitness (Pbest) then P*best*= P and set the best of P*best* as G*best* .
4. Update particles velocity and position equation
5. Stop: giving *gbest*, optimal solution, and repeat until convergence obtained.

The parameters of PSO are chosen as follows:

1. Population size=50
2. Vmax= 20
3. $C_1$and C_2 usually equal to 1.8

K- Means Algorithm and process of implementation

The K-means Clustering Algorithmstarts by picking the number K of centers and randomly assigning the data points x_i to S_i subsets containing N_j data points that minimizes the cost function. It then uses a simple re-estimation procedure to end up with a partition of the data points into clusters containing *N* data points that minimizes the sum squared clustering function. The clustering process terminates when no more data points switch from one cluster to another based on minimization of the following objective function:

$$J_m = \sum_{j=1}^{K}\sum_{i\in S_I}\left\|x_i - c_j\right\|^2 \quad (10)$$

Where $c_j = \frac{1}{N_j}\sum_{i\in s_j} x_i$

This process is implemented in the following algorithm for brain tumor classification.

Step1: Let $X = [(x_{j1}, x_{j2},...,x_{jn})]$, $j = 1,2,...,N$ is the data set that needs to be clustered. The centers 'C' have been randomly initialized from the data set.

Step2: Initially take random centers andthe 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 clusters Sj, and then recomputing the cluster means is chosen as the corresponding center and was updated by using artificial bee colony algorithm.

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

Step 5: The optimized center was sent as inputs to the Proposed Fuzzy C Means based RBFNN algorithm.

Step 6: The proposed Fuzzy C Means based RBFNN algorithm uses the optimized centers as inputs in order to achieve the required clustering.

Step 7: The optimized centers are also sent as inputs to the fast fuzzy c means, Fuzzy c means, and KNN algorithm for the purpose of comparison with the proposed algorithm.

In the proposed work features such as entropy, energy, standard deviation, autocorrelation, mean, variance etc. have been extracted from the MR image signals. After feature extraction it is found that the variance and entropy are the most distinguished features. Therefore, variance and entropy values have been taken for clustering of various image signals. A number of 200 feature vectors are given as input to the Hybrid Fuzzy C Means RBFN algorithm for clustering classification.

RESULTS AND DISCUSSION

A total of 200 images has been taken for training and classification task. It is found from the result that the model RBFNN with PSO training takes near about 11. 214534seconds for clustering optimization. The clustering classification accuracy have been obtained from the model and presented in the table. Also the computational time has been calculated using MATLAB R2017a software.

Table 2 Classification Accuracy of the model

Model	No. of data	Computational time	Classification accuracy
RBFNN -LMS	200	17.251273	94.2
RBFNN -PSO	200	11. 214534	97.9
KNN	200	37.324524	80.3
K-MEANS	200	29.214433	85.2
Fuzzy C Means	200	24.233232	90.5
Fast Fuzzy C Means	200	21.123242	95.8

The fig-6 to fig -8 shows the clustering results of different algorithm. It is found that the Hybrid Fuzzy C means clearly clusters the Beignin and Malignant tumors. Also it is observed that the proposed Fuzzy C Means Based RBFNN model takes lesser computational time as compared to other models.

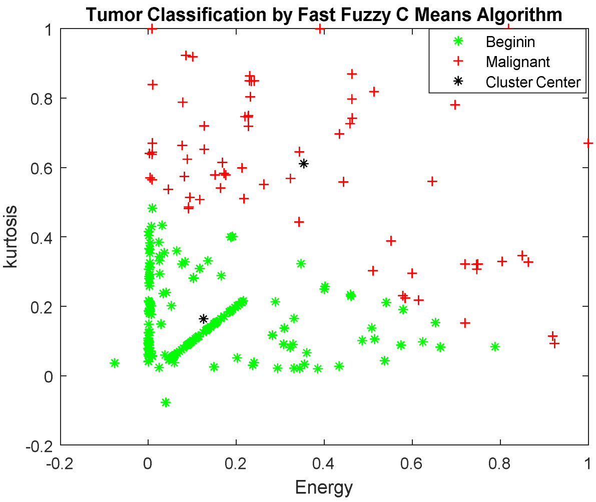

Fig 6 Classification of brain tumor using Fast Fuzzy C Means algorithm

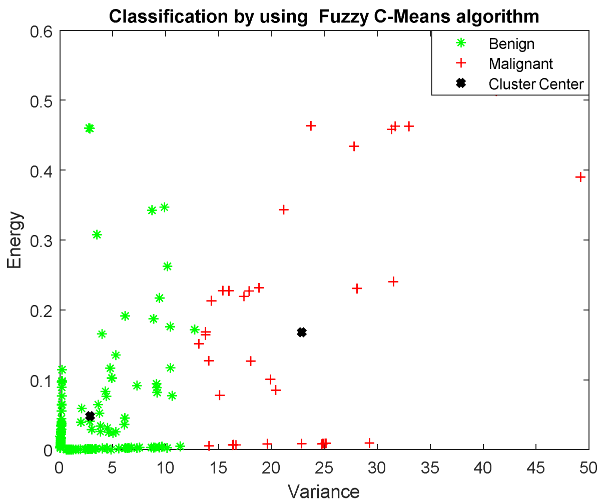

Fig 7 Classification of brain tumor using Fuzzy C Means algorithm

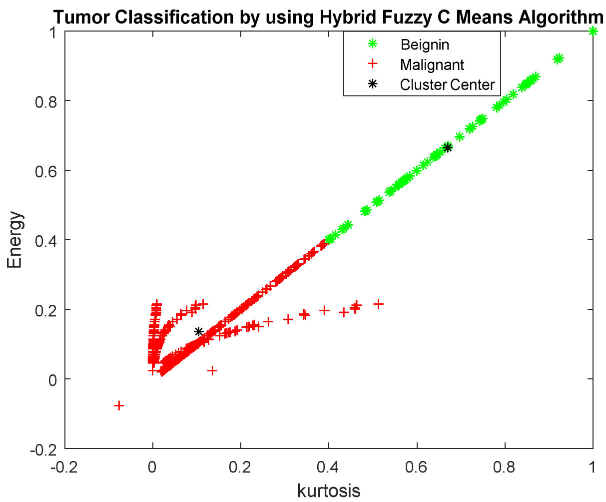

Fig 8 Classification of brain tumor using Hybrid Fuzzy C MeansRBFNN Model

CONCLUSION

The research work shows a better clustering results by considering the two popular types of tumors for classification through clustering, feature extraction and image segmentation. The proposed model has shown the potentiality of clustering of the tumor which was not considered by the researchers previously.The automatic detection and classification using the proposed Hybrid Fuzzy C Means RBFNN model with PSO training is the main purpose of the paper. Images are segmented and features are extracted using wavelet transform at the first step. There are seven features have been considered for the clustering task. The features such as kurtosis, variance, energy and skewness are considered for the clustering task. These features have given adequate classification results. The proposed RBFNN with PSO model has been assigned for the classification and the results were compared with the conventional Fast Fuzzy C Means, Fuzzy C Means, KNN, K-Means approach. From the result it is found that the proposed model provides better clustering result and the computations time obtained as less as compared to other conventional methods

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