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AUTOMATIC CLASSIFICATION AND DETECTION OF BRAIN TUMOR USING HYBRID K-MEANS RADIAL BASIS FUNCTION NEURAL NETWORK AND FAST FUZZY C-MEANS ALGORITHM

Laxmi Priya Nayak*
Satyasis Mishra**
Padmaja Pattnaik***
Debaraj Rana****

Keywords:

RBFNN;
PSO;
Fuzzy c means;
Fast fuzzy c means;
K-Means.

Abstract

This research work presents an automatic detection and classification of brain tumor using a K-Means based Radial Basis Function Neural Network (RBFNN) from the MR images. In the first step the MR images has been segmented by the K- means algorithm and the features are extracted from the images using GLCM (Gray Level Co-occurrence Matrix) feature extraction technique. Further in the second phase the extracted features have been aligned as input to the proposed Hybrid K-Means based Radial Basis Function Neural Network for the classification of brain tumors. The weights of the Radial Basis Function Neural Network are updated by the PSO (Particle Swarm optimization) algorithm and also the centers of the Radial Basis Function Neural Network are chosen by K-means algorithm, so we name the proposed model as Hybrid K-Means based RBFNN model. The malignant and benign tumor has been clustered by the Fast Fuzzy C-Means for visual localization and the performance of the proposed model has been compared with the Fast Fuzzy C-Means, KNN algorithm, and Fuzzy C Means algorithm. The simulation results provide the significance in terms of quality parameters and accuracy.

Author correspondence:

Dr. Satyasis Mishra
School of Electrical and Computing
Electronics and Communication Engineering Program
Adama Science and Technology University, Adama-Ethiopia

* M.Phil Program, Physics, Centurion University of Technology and Management, India
** Electronics and Communication Engineering Program, Adama Science and Technology University, Adama-Ethiopia
*** Department of Physics, Centurion University of Technology and Management, Bhubaneswar, India
**** Department of ECE, Centurion University of Technology and Management, Bhubaneswar, India

1. Introduction

There are mainly two categories of brain tumors are there 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.

Meningiomas [1] 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. Different classifiers such as SVM, K-Means, FCM, RBFNN etc. already been proposed for classification and detection of the brain tumors by the researchers and found results in terms of accuracy and computational time for the cancerous and noncancerous brain tumors.

Nilesh Bhaskarrao Bahadure et al [2] 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. Chaddad [3] 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. Zanaty [4] proposed a methodology for brain tumor segmentation based on a hybrid type of approach, combining FCM, seed region growing, and Jaccard similarity coefficient algorithm to measure segmented gray matter and white matter tissues from MR images. This method obtained an average segmentation score S of 90% at the noise level of 3% and 9%, respectively. Torheim et al. [5], presented a technique which employed texture features, wavelet transform, and SVM's algorithm for effective classification of dynamic contrast enhanced MR images, to handle the nonlinearity of real data and to address different image protocols effectively.

Kumar and Vijayakumar [7] introduced brain tumor segmentation and classification based on principal component analysis (PCA) and radial basis function (RBF) kernel based SVM and claims similarity index of 96.20%, overlap fraction of 95%, and an extra fraction of 0.025%. The classification accuracy to identify tumor type of this method is 94%with total errors detected of 7.5%.Sharma et al.[8] have presented a highly efficient technique which claims accuracy of 100% in the classification of brain tumor from MR images. This method is utilizing texture-primitive features with artificial neural network (ANN) as segmentation and classifier tool. Cui et al. [9] applied a localized fuzzy clustering with spatial information to form an objective of medical image segmentation and bias field estimation for brain MR images. In this method, authors use Jaccard similarity index as a measurement of the segmentation accuracy and claim 83% to 95% accuracy to segment white matter, gray matter, and cerebrospinal fluid. Wang et al. [10] have presented a medical image segmentation technique based on active contour model to deal with the problem of intensity in homogeneities in image segmentation. T.Gopi Krishna and S.Mishra[11] proposed a

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detection and classification of Brain Tumor from MRI Medical Image using Wavelet Transform and PSO based LLRBFNN Algorithm. P. K. Nayak and S. Mishra [12], have presented a LLRBFNN model and a modified teaching–learning-based optimization for classification of multiple power signal disturbances from which the proposed model has been inspired to classify the brain tumor. Deepa and Arunadevi [13] have proposed a technique of extreme learning machine for classification of brain tumor from 3D MR images. This method obtained an accuracy of 93.2%, the sensitivity of 91.6%, and specificity of 97.8%. Sachdeva et al. [14] have presented a multiclass brain tumor classification, segmentation, and feature extraction performed using a dataset of 428 MR images. In this method, authors used ANN and then PCA-ANN and observed the increment in classification accuracy from 77% to 91%.

The above literature survey has revealed that some of the techniques are applied to obtain segmentation only; some of the techniques are invented to obtain feature extraction and some of the techniques are invented to obtain classification only. This paper proposes a novel Hybrid K-Means based RBFNN model clustering technique to cluster the benign and malignant tumors. Fuzzy clustering is one of the soft segmentation methods have been successfully applied in image clustering and segmentation problem. Among the fuzzy clustering methods, Fuzzy C-Means (FCM) algorithm is the most popular method used in image segmentation because it has robust characteristics for ambiguity and can retain much more information than hard segmentation methods [15]. Although the conventional FCM algorithm works well on most noise-free images, it is very sensitive to noise and other imaging artefacts, since it does not consider any information about spatial context. To compensate this drawback of FCM, a pre-processing image smoothing step has been introduced. However, by using smoothing filters important image details can be lost, especially boundaries or edges. Moreover, there is no way to control the trade-off between smoothing and clustering. Thus, many researchers have incorporated local spatial information into the original FCM algorithm to improve the performance of medical image segmentation [16]. In addition to the incorporation of local spatial information, the centroid initialization process for the conventional FCM has made for performance improvement. But it is found the Fast Fuzzy C Means and K-Means clustering algorithm shows non adequate classification results.
To have better classification result the K-Means based RBFNN model has been proposed. The features have been extracted from the MR images are send as input to the model and the classification results have been obtained. The K-Means RBFNN model weights are updated by LMS algorithm and PSO algorithm. The centers are optimized by K-Means algorithm and the comparison results have been presented in the result and discussion section.
This paper organizes follows: the Section-2 presents the Research method and the proposed model for classification, Fast Fuzzy C Means algorithm, Section 3 presents the results followed by the conclusion and reference.

2. Research Method

2.1 Fuzzy C Means Algorithm

In FCM a data sample is assigned with a membership value based on its similarity with the cluster center. The membership values are between 0 to 1 and more the similarity, higher the membership value.

. 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

In Fuzzy C means clustering we determine the cluster center v_i and the membership matrix U and we thus determine distinct clusters. Fuzzy C Means [17]-[20] method is based on minimization of the following objective function:

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

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 taking the derivative of the equation and make it equal to zero by using Lagrange method, the following equations are achieved

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

(2)

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

2.2 Fast Fuzzy C Means Algorithm

According to Fast fuzzy c means algorithm, 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

$$j = \sum_{k=1}^{N} \sum_{i=1}^{L} u_{ik}^m \|x_k - C_i\|^2$$

(3)

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

In many real situations, overlapping clusters reduce the effectiveness of crisp clustering methods. Ruspini first proposed the notion of fuzzy partition, where samples may partially belong to several clusters through the idea of partial membership degrees.

Minimization of equation (3) is obtained by an optimization technique that successively updates the cluster centers C_i and partition matrix U by using the formula

$$C_i = \frac{\sum_{k=1}^{N} u_{ik}^m x_k}{\sum_{k=1}^{N} u_{ik}^m}$$

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(4)

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

(5)

The choice to first initialize a random partition matrix or the cluster centers is let to the user, both being used in the literature.

Centroids initialization:

In this research work a new, efficient, yet simple, manner of initializing the 'c' cluster centers that we call Ordering-split. For each p-dimensional sample x_k, we define its relative mean by

$$m_k = \frac{1}{p}\sum_{j=1}^{p} x_{kj}$$

(6)

so that we obtain the n-dimensional vector $m = (m_1, m_2, \ldots m_n)$. Note that we are working on features coming from each channel of an image so that the scale of individual features does not differ. If the features do not hold this property, normalization is required. Let σ be the permutation function σ such that $m_{\sigma}(k)$ is an ordered and increasing sequence. We propose to split the n relative means as follows.

Assuming that the clusters are equally distributed, we uniformly split the n-dimensional vector m into c groups. In other terms, we set $c+1$ indices, say $l_0, l_1..l_c$,such that the c differences $(l_i - l_{i-1})$ are roughly equal. More formally, each index is given by

$$l_i = i * \lfloor n/c \rfloor$$

(7)

Where $\lfloor . \rfloor$is the floor function. We iteratively build c subsets S_i of n as follows

$$S_i = \{l_{i-1} + 1, \ldots.. l_i\}$$

We obtain the subset of indices in each cluster by applying the inverse function:

$$C_i = \sigma^{-1}(S_i)$$

(8)

Finally, each cluster center is computed using:

$$v_i = \frac{1}{|C_i|}\sum_{j \in C_i} x_j$$

(9)

Where $|C_i|$ is the cardinality of C_i .

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2.3 KNN Algorithm

Typically the object is classified based on the labels of its *k* nearest neighbors [22] 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:

$$d(x,y)=\sum_{i}^{k}\sqrt{(x_i-y_i)(x_i-y_i)'} \tag{10}$$

2.4 Research Flow Diagram

The research work is focussing 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. 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 for the comparison of classification accuracy.

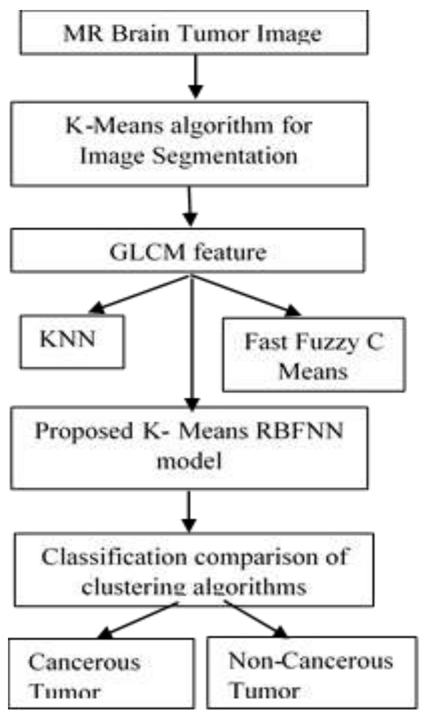

Fig:1 Research Flow Diagram

The MRI datasets has been retrieved from the Harvard medical school architecture and Alzheimer's disease Neuroimaging Initiative (ADNI)[11] public database (http://adni.loni.usc.edu/) and Nidan medical center, Bhubaneswar. A total of 100 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 are extracted by the GLCM feature extraction technique [2] from the image and the normalized feature table is presented. The statistics feature formula for some of the useful features is mentioned below.

(1)Mean(M). $M = \left(\frac{1}{m \times n}\right)\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} f(x,y)$

(2) Standard Deviation (SD). $SD(\sigma) = \sqrt{\left(\frac{1}{m \times n}\right)\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}\left(f(x,y) - M\right)^2}$

(3) Entropy (E). Entropy is calculated to characterize the randomness of the textura limage and is defined as $E = -\sum_{x=0}^{m-1}\sum_{y=0}^{n-1} f(x,y)\log_2 f(x,y)$

(4)Skewness(S_k). The skewness of a random variable X is denoted as (X) and it is defined as $S_k(X) = \left(\frac{1}{m \times n}\right)\frac{\sum\left(f(x,y) - M\right)^3}{SD^3}$

(5)Kurtosis (S_k). For the random variable X, the Kurtosis is denoted as $K_{urt}(X)$ and it is defined as $K_{urt}(X) = \left(\frac{1}{m \times n}\right)\frac{\sum\left(f(x,y) - M\right)^4}{SD^4}$

Table -1 Normalized Feature Extraction Table

Images	Std.Dev	Mean	Entropy	Variance	Skewness	Kurtosis	Energy
Img-1	0.1469	0.0322	0.2052	0.0031	0.90198	0.84224	0.23358
Img-2	0.0425	0.002	0.0207	0.0001	0.428481	0.13517	0.0144
Img-3	0.0839	0.0086	0.0711	0.0005	0.575785	0.24065	0.06213
Img-4	0.1112	0.0169	0.1235	0.0011	0.441104	0.21941	0.12249
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

2.5 Image Segmentation Using K-Means Algorithm

Image segmentation [2] methods fall into different categories: Region based segmentation, Edge based segmentation, and Clustering based segmentation, thresholding, Artificial neural network, feature-based segmentation. Clustering of an image is one of the good techniques, which is used for segmentation of images. After extraction of features, these features are put together into well-separated clusters based on each class of an image. The clustering algorithm aim is to develop the partitioning decisions based on initial set of clusters that is updated after each iteration.

K-Means is one of the relaxed unsupervised erudition algorithms that illuminate the well-known clustering issue [23,24]. The methodology trails after a straightforward and simple approach to group a given information set through a certain number of groups (expect k groups) that have been established beforehand. The principle idea is to characterize k centroids, one for each group. The objective function is shown below; and thus, the algorithm aims to reduce the squared error in this function:

$$J_m = \sum_{j=1}^{K} \sum_{i \in S_I} \left\| x_i - c_j \right\|^2 \tag{11}$$

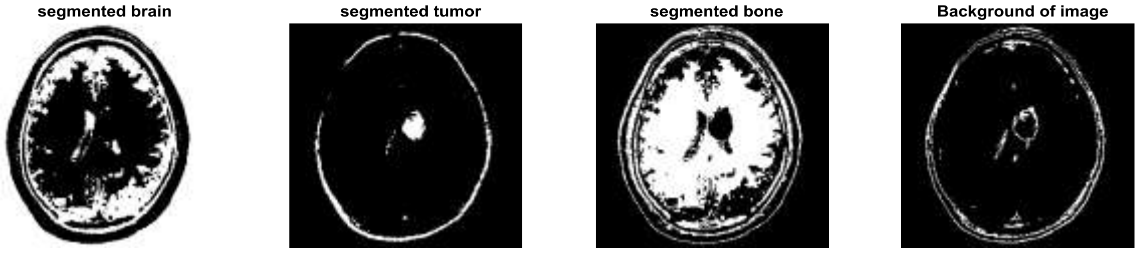

Fig 2. K-Means image segmentation

2.6 Proposed PSO based RBFN algorithm

The RBFNN[25] 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 by PSO[26] during training .Here, the center and width of Gaussians are selected using K- 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.

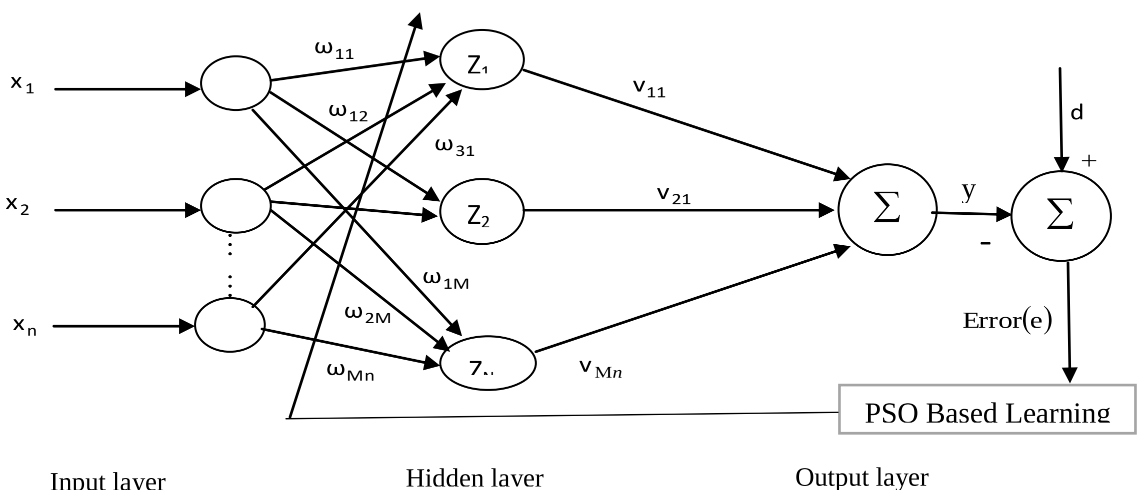

Fig: 3 PSO Based Radial Basis Function Neural Network

In this model, it is noticed that in RBFNN 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

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

(12)

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

$$y = \sum_{n=1}^{N} (v_{11}x_1 + v_{12}x_2 ------ v_{Mn}x_n).e^{\left(\frac{-\|(x_N - C_M)\|^2}{2\sigma_M{}^2}\right)} \quad (13)$$

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 [25]. 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.
2.6.1 Weight Updation by Particle swarm optimization:

The PSO [26] algorithm is a population based search algorithm based on social behavior of birds within a flock. PSO requires only primitive mathematical operators and is computationally inexpensive in terms of both memory requirements and speed. The features that drive PSO are social interaction. Individuals (particles) within the swarm learn from each other and based on the knowledge obtained move to become more similar to their better neighbors. The structure of the PSO is determined through the formation of neighborhoods.
The updated PSO equations described are as follows:
The velocity update equation is given by

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

(14)

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

(15)

And the position update equation is given by
PSO Process follows as:

1. Initializing particles with random position and velocity vectors.
2. Evaluating fitness function for each particle's position ..
3. If fitness is better than fitness then P*best*= P and set the best of P*best* as G*best*
4. Update particles velocity and position equation

The parameters of PSO are chosen as follows:

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

2.6.2 Steps of K-Means Based RBFN algorithm implementation:

Clustering of an image is one of the good techniques, which is used for segmentation of images. After extraction of features, these features are put together into well-separated clusters based on each class of an image. The clustering algorithm aim is to develop the partitioning decisions based on initial set of clusters that is updated after each iteration. The K-Means [26] Clustering Algorithm starts by picking the number K of centres 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:

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

(16)

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

Algorithm:

k-means. The k-means algorithm for partitioning, where each cluster's center is represented by the mean value of the objects in the cluster.

Input: k: the number of clusters, D: a data set containing $n$objects.

Output: A set of k clusters.

Method: (1) randomly choose k objects from D as the initial cluster centers;

(2) Repeat

(3) (Re) assign each object to the cluster to which the object is the most similar, based on the mean value of the objects in the cluster;

(4) Update the cluster means, i.e., calculate the mean value of the objects for each clusters; (5) until no change;

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

Step1: Let $X = \{(x_{j1}, x_{j2}, \ldots, x_{jn})\}, \quad j = 1,2,\ldots,N$ 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 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 clusters, and then the cluster means is chosen as the corresponding center and was updated by using K-Means 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 K-Means based RBFNN algorithm.

Step 6: The proposed K-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 K-Means RBFN algorithm for clustering classification.

3. Results and Analysis

A total of 200 images has been taken for training and classification task. It is found from the result that the model K-Means based RBFNN with PSO training takes near about 12.217834 seconds for clustering optimization. The clustering classification accuracy have been obtained from the model and presented in the table.

Table-2: Classification Accuracy of the model

Model	No. of data	Computational time	Classification accuracy
KNN	**200**	**32.124523**	**81.1**
K-MEANS	**200**	**27.116431**	**87.3**
Fuzzy C Means	**200**	**22.273292**	**91.1**
Fast Fuzzy C Means	**200**	**19.123242**	**96.4**
RBFNN -PSO	**200**	**12. 217834**	**98.6**

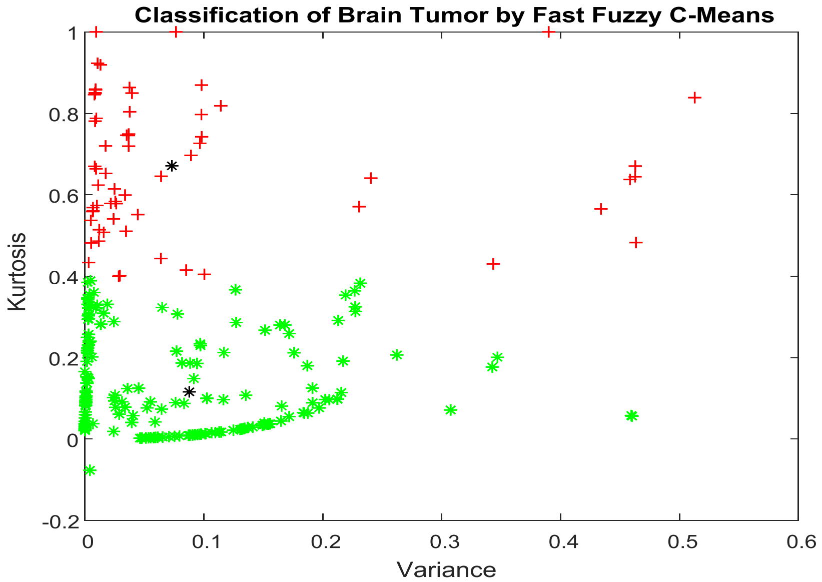

Fig : 4 Classification of brain tumor using Fast Fuzzy C Means algorithm

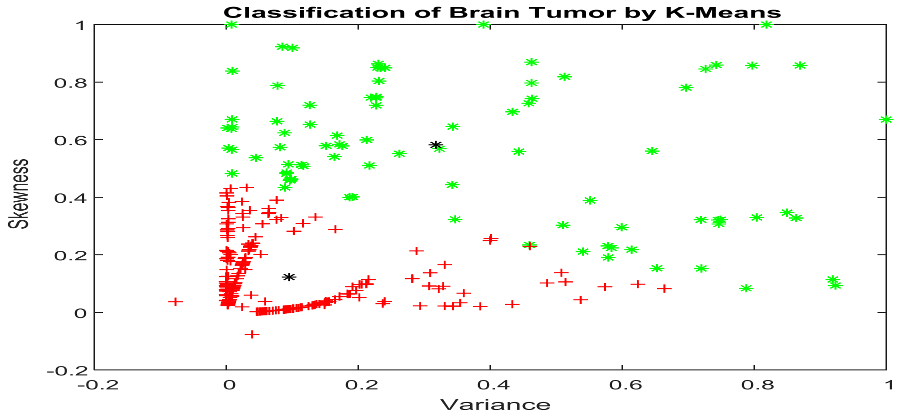

Fig : 5 Classification of brain tumor using K- Means algorithm

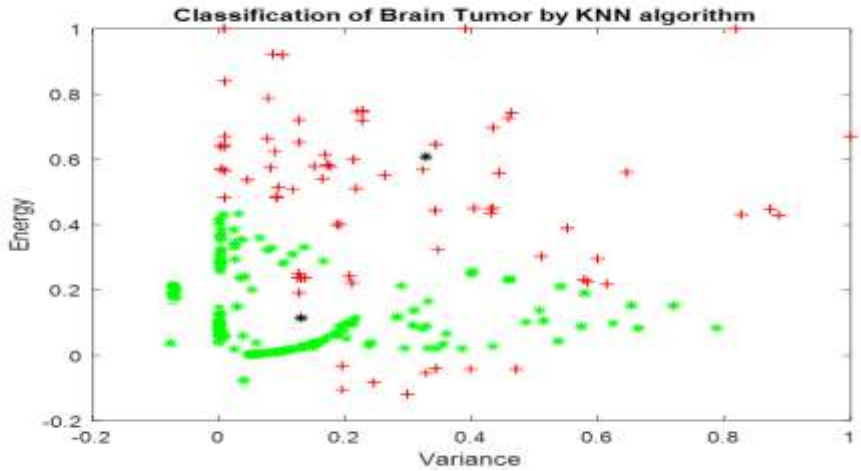

Fig : 6 Classification of brain tumor using KNN algorithm

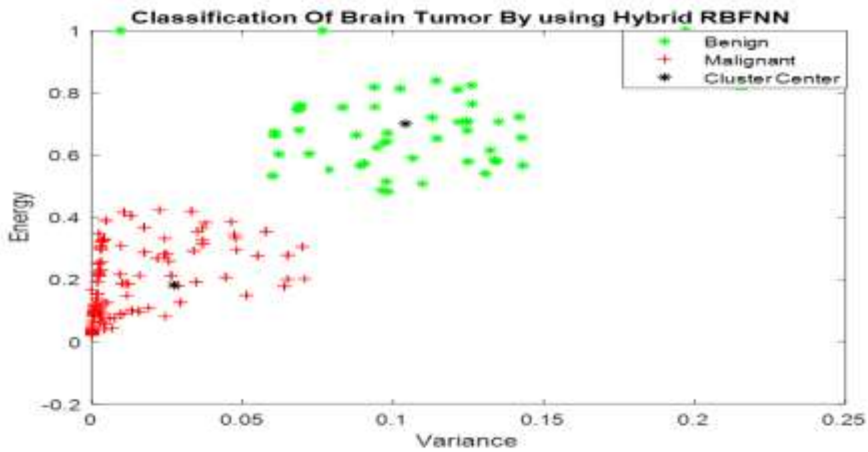

Fig : 7 Classification of brain tumor using Hybrid K-Means based RBFNN Model

4. Conclusion

This paper presents the clustering of brain tumors which provides adequate classification results. The research work shows a better clustering results 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 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 K-Means based 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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