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Efficient analysis of Brain Tumor from MRI image using K-means clustering and Neural Network

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ABSTRACT

Background: Brain tumor is a group of growing abnormal cell present in the brain. The treatment of this disease may vary from patient to patient and the effects of the treatment reflect to each patient are different chance of curing the disease can be increased only if the tumor is identified and classified in an early stage with good accuracy. Human effort of examining the samples are time consuming, not much accurate and this may result in diagnosis error. **Objective:** In order to overcome these drawbacks, an automatic support system is proposed for the detection and classification of brain tumor in a better and accurate manner. This system comprises of feature extraction followed by segmentation and finally the classification process.Using the K-means clustering algorithm, the MRI images are segmented where the brain tumor portion are outlined. Then the GLCM technique extracts the extracts the significant features from the segmented image and the extracted features are given to the classification process where the artificial neural network is used to classify the given image with the extracted features into different stages using the training dataset. **Results:** The performance of the proposed system is examined with respect to the classification accuracy. **Conclusion:** For a classification of brain tumor a new method has been proposed in this paper, which makes use of K-means segmentation and Artificial Neural Network.The proposed method has made use of neural network to perform the necessary calculation automatically.

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INTRODUCTION

In recent years, there is an clear observation from the instance growth of various research work in the field of tumor diagnosis and also the tumor spreads in world population(Santhosh Kumar, and Jmaes Albert, 2014).The biomedical image analysis and pattern recognition problems are rectified efficiently by the application of machine learning techniques. Novelty detection has potential applications in many problem domains such as condition monitoring or medical diagnosis. Among the techniques developed for classification, popular ones include Bayesian classification, Neural Networks, Generic Algorithms and Decision Trees. Various types of classification techniques are used by the researchers to analyze the MRI data (K. Arthi & A. Tamilarasi, 2009). Those techniques are the K-Nearest Nrighbors (KNN), Bayes classifier, Artificial Neural Networks (ANN), (S.Chaplot, L.M.Patnaik *et al*., 2006.) Support Vector Machines (SVMs), Back Propagation Network (BPN), Artificial intelliegence (Ibrahiem M, Ramakrishnan S., 2008) and Expectation Maximization (EM) as the statistical classification scheme. Inspired by biological neural networks, Artificial Neural Networks are developed to mimic the characteristics such as robustness and fault tolerance. To perform the classification task of medical data, the neural network is trained. Neural networks have emerged as an important tool for classification(Torii M. and Hagan M.T, 2000&R. B. Dubey , M. Hanmandlu, 2009). Neural networks receive an extensive application in biomedical systems and have wide application in cardiology, gastroenterology, Pulmonology, oncology, neurology, brain function, ophthalmology and radiology (Fan-Hui kong,2009).Segmentation is more important aspects of classification and it makes the classification process much easier (8). The increased importance of automated computer diagnosis for anatomical brain mapping of the quantitative brain image and MR image analyzing

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methods leads to requirement of validating and evaluating the effect of the images. The categorization of brain tumor process helps the radiologists to explore the better accuracy from the delineation of MRI findings(Messen W, Wehrens R *et al*., 2006).The combination of kNN and the artificial neural network is implemented for the tumor diagnosis in early stage, but still needs an effective method for the feature identification for improved classification (E.A. El-Dahshan, T. Hosny *et al*.,2010). Diagnostic imaging with suspected intracranial neoplasia is fourfold: localization, lesion detection, determination of tumor extension and characterization. In contrast to CT, MR imaging allows more precise determination of lesion location and demonstrates better subtle mass effects, particularly along the cerebral convexities (DeepaVerma and Dhirendra Kumar Jha., 2014). MR imaging is popular for differentiating the tumor from perifocal edema, which is used to define the extent of tumor and prevents the harmful ionizing radiation, thus never leads to the precise histological diagnosis.

Methodology:

A. Imaging Data:

Real Time MRI images are collected from Metro Scans & Laboratory, a unit of Trivancore Healthcare Pvt Ltd, Trivandrum, India. Experiments are conducted on MR images collected from 1000 different patients with tumor as well as non tumor images. Each patient has 2 sequences of MR images T1 and T2. Then we used neural network to classify the tumors.Fig.1 shows some examples of normal and abnormal subjects. In abnormal there are two stages one is benign and the second one is malignant. Actually, this two stage of tumors having a differentway of structure, for example, if the consideration is benign the tumor will occur in one place, it won't spread. Similar way, if you consider malignant the tumor won't occur in single place it will spread to the whole image.

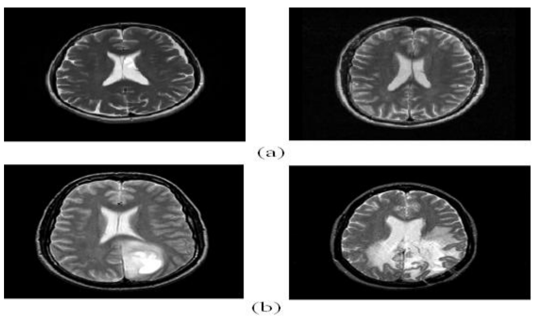


Fig. 1: Examples from (a) normal (b) abnormal subjects.

B. Preprocessing:

Some images of the dataset were darker rather than others. This is because of data acquisition scanner problems. These kind of problem you can't rectify by replacing the whole unit, because MRI scanner is more expensive, so we are implementing some image processing technique to suppress this kind of problem and the scans are corrected for intensity non-uniformity using histogram equalization. Fig.2 depicts an example of dark MR image after and before preprocessing.

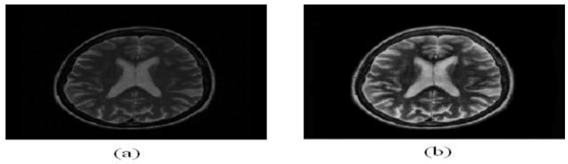


Fig. 2: (a) Original image (b) Image after pre-processing.

When we supply a desired histogram, histeqselects to minimize the grayscale transformation T

$$c_1{}^{(T(K))} - c_0{}^{(K)} \quad (1)$$

Wherec_0 - cumulativehistogram of A.Similarly the c_1 - cumulative sum of histeq for all intensities k.

The grayscale minimization is subjected to the constraints, where the transformation T must be a monotonic form and the c_1(T(a)) do not overshoot the c_0(a) by more than the half of the distance between the 'a' and histogram counts, thus the histeq utilizes this transformations in order to map the gray levels in X/ color maps to their new values.If we do not specify histeq, then createa flat hgram, as

$$hgram = ones(1, n) * \frac{prod\ (size\ (A))}{n} \quad (3)$$

and then apply the previous algorithm.

C. Segmentation:

Most of the clustering problems are solved by the K-Means unsupervised learning algorithm which follows a simple procedure by classifying the given data into a certain number of clusters and fix the priori (M. Varma and B. R. Babu., 2009) and(Qurat-ul-ain ,GhazanfarLatif *et al*., 2010.). Defining of k centroids of each cluster is one of the main ideas of K-Means clustering algorithm. Thus, these centroids must be placed in a cunning way by placing them far away to each other, the reason where the different location leads to different results.Then the points belonging to the corresponding data set are selected and link it to the nearest centroid.When there is no waiting point, the process of the first step is completed, then the points of the clusters are needed to recalculate the k new centroids as the bar center of the clusters resulting in the previous step.After gaining the k new centroids, a creation of new binding is made in between the nearest new centroid and data set points, with the generation of the loop. As a result of this loop generation, it is clear to identify the change in the location of k centroids. Finally, the K-Means algorithm focuses to minimize the objective function in the situation of squared error function. The objective function can be stated as

$$j = \sum_{j=1}^{k} \sum_{i=1}^{m} \left\| X_i^{(j)} - c_j \right\|^2 \quad (4)$$

Where $\left\| X_i^{(j)} - c_j \right\|^2$ is the selected distance measure between the clusterand a data point $X_i^{(j)}$. The Center c_j is anindicator of the distance between the n data points from their respective cluster centers. The algorithm consists of the following steps:

Step 1: The k points are placed in the space where the objects are clustered. These points resembles to the initial group of centroids.

Step 2: The group of closest centroids is assigned by separate objects.

Step 3: After assigning all the objects, the positions of the k centroids are calculated once again.

Step 4: Repeat the process of step 2 and 3 until there is no change in the position of the centroids.

This algorithm forms a group by collecting all the separated objects, where the metrics are minimized and calculated(S.Sivakumar and C.Chandrasekar., 2014).Always the procedure of K-Means algorithm is terminated and it cannot be able to identify the optimal configuration, that arecorresponding to the minimum global objective function(C. M Wang, M. J. Wu *et al*., 2009).The algorithm is relatively sensitive to the cluster centers those are selected randomly and the operation of K-Means algorithm is processed for many times in order to reduce the effect. Therefore, it is a simple algorithm which is utilized to handle various types of problem domains and it can efficiently work for the randomly generated data points.The problems of K-Means are solved by the popular heuristic which is based on the simple iterative scheme, that helps to find out the local minimal solution.The block diagram of K-Means is represented as

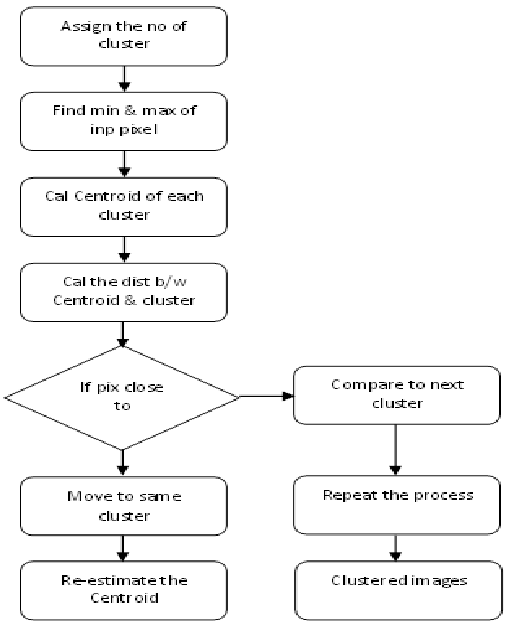
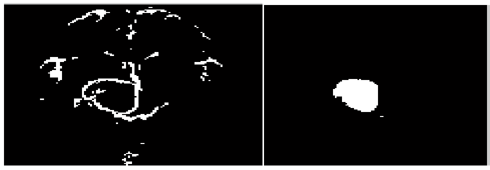


Fig. 3: Block diagram of k-means clustering.

Cluster 1 Cluster 2



Cluster 3 Cluster 4

Fig. 4: Kmeans segmentation results.

D. Feature Extraction:

1. Shape based features:

Shape based features such as circulatory, irregularity, area, perimeter, shape index are extracted from the segmented regions(S.N.Sivanandam,S.Sumathi,S.N.Deepa., 2009).

Area of the region in an image can be described as the number of pixels confined inside the segmented region including the boundary. Hence, the area extracted from a segment is the number of pixels inside the segmented region.

Perimeter is a path that surrounds a two-dimensional shape in consideration. Perimeter of the segmented region can be described as the number of pixels in the boundary line of the region.

Solidityis indicated to the pixels proportion of the convex hull, that are computed as the Area/Convex area. This property is supported only for the application of 2-D input label metrics.

Eccentricityis said to be as a scalar which determines the ellipse. Where these ellipses consist of the second moment as the region.The ratio of the eccentricity is determined by the distance between its major axis length and the ellipse foci.

Thus the value generated between this major axis length and ellipse foci will in the range of 0 and 1. Where the 0 eccentricity indicated the actual circle and the 1 eccentricity represents the line segment. Thus, these 0 and 1 eccentricities are said to be as the degenerate cases.

2. Texture based features:

Contrast, Correlation, Entropy, Energy, Homogeneity, cluster shade and sum of square variance are the texture based features extracted from the segmented region.

Contrast can be defined as the difference in luminance and/or color of the image. Contrast is determined by the difference in the brightness of the object, in color and other objects.The Contrast has been expressed as,

$$contrast\ I = \sum\sum (x-y)^2 p(x-y) \quad (5)$$

Correlation refers to any of a broad class of statistical relationships involving dependence.

Correlation of the image is defined the ratio between covariance and the standard deviation.

$$Cov(Y,Z) = E\big[\big(Y - E(Y)\big)\big(Z - E(Z)\big)\big] \quad (6)$$

Entropy (en) it's a statistical measure of randomness that can be used to characterize the texture of the input image.

$$en = -\sum_x \sum_y p(x,y) log p(x,y) \quad (7)$$

Energy (eg) is used to describe a measure of information present in the segmented region. The energy can be given by:

$$eg = \sum_x \sum_y p(x,y)^2 \quad (8)$$

Homogeneityis said to be as the homogenous state.Related to the field of science, the homogeneity is a substance of the constituents with the same nature, consisting of the similar parts or the elements of similar nature. It can be stated by the generalized formula:

$$Homogenity = \sum_{i=1}^{Ng} \sum_{j-i}^{Ng} P(i,j)^2 \quad (9)$$

3. Intensity based features:

Mean, Variance, Standard Deviation, Median Intensity, Skewness and Kurtosis are intensity based features that are extracted from segmented regions. After features extraction, important features will be selected using linear discriminant analysis (LDA) to classification purpose.

Mean (μ) is simply the averageof the objects in consideration. Mean of the region is found out by adding all the pixel values of the region divided by the number of pixels in the region.

Variance (σ^2) measures how far a set of pixels of the image is spread out. The representation of the zero variance states that the values are identical in nature.

$$\sigma^2 = E(x^2) - \big(E(x)\big)^2 \quad (10)$$

Standard deviation (σ) is the square root of the variance. It also measures the amount of variation from the average. The data points that are close to the mean point are stated asthe lowest standard deviation.

Median is said to be as the numerical value which separates the higher half of pixel values from the lower half. The median is calculated by arranging all the observations from lowest to highest values in an order and then picks the middle one.

Once all the features are extracted, then only we can perform Neural Network for database training and classification.

E. Neural Network:

Neural network contains different architectures with large number of classes (18).In most of the situations the problem is created by approximating the static nonlinear, mapping *f* □**x**□ □ witha neural network fNN(**x**), where$X \in R^k$.

Efficient neural network in the case of function approximations is the Radial Basis Function (RBF) and Multi Layer Perceptron (MLP) networks. Here the MLP networks are concentrated.

A MLP consists of an input layer, several hidden layers, and an output layer. Node *i*, also called a neuron, in a MLP network is shown in Fig. 1. It includes a summer and a nonlinear activation function *g*.

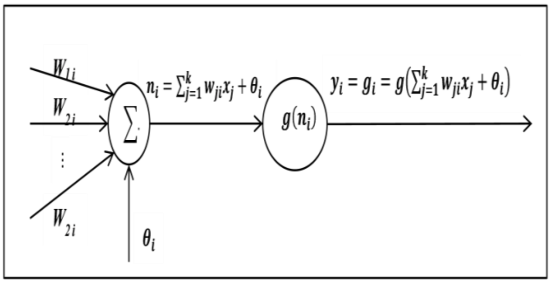


Fig. 5: MLP network with single node.

The inputs, 1,..., *k x k* = *K* to the neuron augmented by the weights *ki w*, thenadded up together with the constant bias termθ_i. Thus, the resulting term$n_i$is the input to the activation function *g*. The activation function is selected originally to be as the relay function, but in the case of mathematical convenience the sigmoid function or the hyperbolic tangent (*tanh*) is used commonly. Hyperbolic tangent is represented as

$$\tanh(x) = \frac{1-e^{-x}}{1+e^{-x}} \quad (11)$$

The output of node *i* become

$$y^i = g_i = g\left[\sum_{j=i}^{k} w_{ji} x_j + \theta_i\right] \quad (12)$$

By connecting several nodes with series and

MLP network is generated by parallel and series with the linkage of numerous nodes. Demonstration of the typical network is given in the Fig. 6.

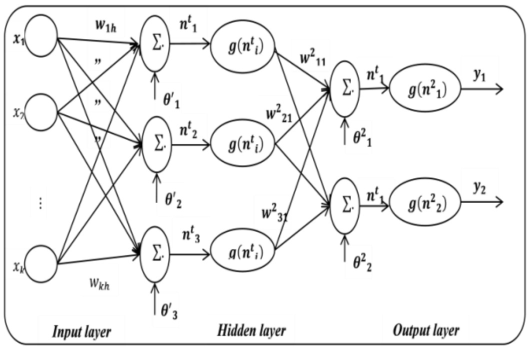


Fig. 6: The MLP network with one hidden layer.

Here a single activation function *g* is used i both layers. The superscript of *n*, □ □ ,or *w*refers to the layer, first or second.

RESULT AND DISCUSSIONS

As shown in table2, we took 3 images such asNormal, Benign and Malignant. And we extracted some features like shape, texture and intensity. Forshape feature, we extracted 4 parameters.For texture feature, we extracted 5 parameters and finally for intensity based feature,the extraction of 4 parameter, and totally 4 + 5 + 4 = 13 parameters.

As we discussed earlier in section 1, we have nearly 2000 no of images. In this database we have 600 normal, 700 benign and 700 malignant images. Instead of training all those 2000 images we trained only 1500 images choosing 500 from normal, 500 from benign and 500 from malignant. Remaining 500 images we kept for testing purpose. And we perform our algorithm to test those 500 set of images and we had calculated accuracy of our system.

Table 1: Target vector for database images.

Features	Normal	Benign	Malignant
Area	53	1.978	5
Perimeter	73.8995	0.1872	6.2426
Solidity	0.5889	0.0009	1
Eccentricity	0.9982	0.0006	0.9013
Contrast	0.2691	0.0001	0.3624
Correlation	0.9453	0.001	0.9461
Entropy	5.2701	0.0062	3.7749
Energy	0.3485	0.0002	0.3769
Homogeneity	0.9346	0.0009	0.8897
Mean	49.7329	0.0813	43.6624
Variance	4.4445	0.0042	6.8676
Std	51.7305	0.0611	66.1598
Median	13.0055	0.0205	9.9195

We used Supervised Neural network,and so the output of this system should be defined by user.For example,in our case we used 500 normal images, 500 benign and 500 malignant images. Table 1 shows the assigned target vector for the databases.

Table 2: Feature extraction of different brain images.

S.no	Target vector for database Training					
1	Normal	1	Benign	2	Malignant	3
2	Normal	1	Benign	2	Malignant	3
3	Normal	1	Benign	2	Malignant	3
4	Normal	1	Benign	2	Malignant	3
.	.	.	.	.	.	.
.	.	.	.	.	.	.
500	Normal	1	Benign	2	Malignant	3

The value 1 is assigned for all normal images in database, 2 for all benign images in the database and 3 for all malignant images in the database. The details of target vectors for our database isshown in table 1.

The features are calculated for normal, benign and malignant images. Also, classify whether the test image is normal or benign or malignant, but instead of this manual classification, we perform neural network for making automated system. Feature extraction of different brain imagesis shown in table 2.

Table 3: Distribution of data.

Class	Normal	Benign	Malignant
Training	500	500	500
Testing	100	200	200

Out of 2000 images, 1500 images have been chosen for training and 500 for testing. In the training images 500 are normal, 500 are benign and the remaining 500 is malignant. In the 500 testing images,100 are normal, 200 are benign and 200 are malignant as depicted in the Table 3

Table 4: Classification of Test data.

Class	Normal	Benign	Malignant
Yes	98	197	199
No	2	3	1

The Classification of test data details is shown in table 4. Out of 100 images tested under normal condition. The proposed system can classify the stages correctlu with an accuracy of 98%. Out of 200 benign images tested, the proposed system can classify the stages correctly in197 images and 3 are not classified correctly. Thus, it has an accuracy of 98.5%. Similarly out of 200 malignant images tested, the proposed system can classify correctly in197 images and 3 are not classified correctly. Thus, it has an accuracy of 99.5%. The accuracy is obtained from

$$Accuracy = \frac{Result\ \ of\ \ our\ \ proposed\ \ system}{No\ od\ database\ \ image}\ X\ 100\ (13)$$

The percentage of accuracy is represented in Figure 7.

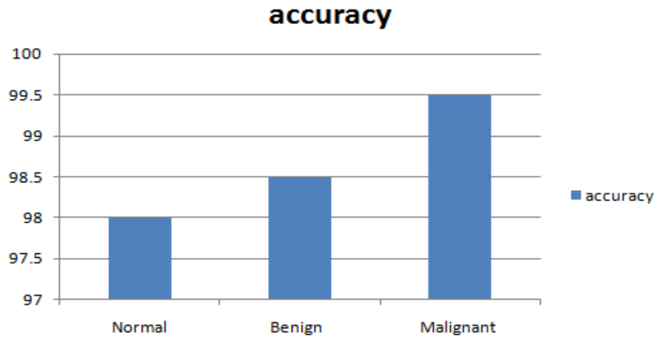


Fig. 7: Proposed method accuracy in all categories of brain image.

Neural networks are usually trained by epoch. An epoch is a complete run when all the training examples are presented to the network and are processed using the learning algorithm only once.The best model is the one with the minimum description length. The total description length *E*MDL has three terms: code cost of coding the input vectors, the model cost for defining the reconstruction method, and reconstruction error due to reconstruction of the input vector from its code.

The goal is to estimate an unknown true target function in regression problems, or posterior probability *P(y|**x**)* in classification problems. In VC theory, it is to find the target function that minimizes prediction risk or achieves good generalization. Figure 8, shows the performance chart of neural network training.

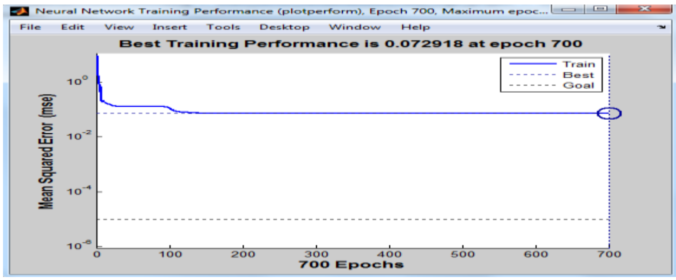


Fig. 8: Neural network Training Performance chart.

Conclusion:

For a classification of brain tumor a new method has been proposed in this paper, which makes use of K-means segmentation and Artificial Neural Network. Out of the 2000 images chosen 1500 images have been trained and 500 tested. In the test images 100 belong to normal category and 200 belong to benign and the remaining 200 are malignant in the category. Test results shows 98%, 98.5% and 99.5% accuracy for normal, benign and malignant respectively. The proposed method has made use of neural network to perform the necessary calculation automatically.

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