ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 6, Issue 4, April 2018

Brain Tumor Classification and Segmentation using PNN & FCM Clustering

Shilpa B. Sanghavi[1] Dr. R.J. Shelke[2]

P.G. Student, Department of Electronics Engineering, Walchand Institute of Technology, Solapur, Maharashtra, India[1]

Sr. Professor, Department of Electronics Engineering, Walchand Institute of Technology, Solapur, Maharashtra, India [2]

ABSTRACT: Automatic and early defects detection in Brain MR images is very important in many diagnostic & Therapeutic applications. Tumor segmentation and classification is very hard because of high quantity data in MR images and blurred boundaries. This work has introduced one automatic brain tumor detection method to increase the accuracy & decrease the diagnosis time and thereby replace conventional invasive and time consuming techniques such as biopsy, lumbar puncture & spinal tap method. The goal is classifying tumors into two classes of normal and abnormal. This method involves- i]Wavelet Decomposition (db4) ii] Feature extraction iii] Classification iv] Segmentation. This method has been applied on real MR images, and accuracy of classification using PNN as classifier is found to be nearly 100%.

KEYWORDS: MR Images, GLCM, Feature Extraction, DWT, Probablistic Neural network (PNN).

I. INTRODUCTION

Brain tumor is any mass that results from an abnormal and an uncontrolled growth of cells in the brain. Its threat level depends on a combination of factors like the type of tumor, its location, its size and its state of development. Brain tumors can be cancerous (malignant) or non-cancerous (benign). Benign brain tumors are low grade, non-cancerous brain tumors, which, grow slowly and push aside normal tissue but do not invade the surrounding normal tissue. Whereas, malignant brain tumors are cancerous tumors, which grows rapidly and invade the surrounding normal tissues.

Many diagnostic imaging techniques can be performed for the early detection of brain tumors such as Computed Tomography (CT), Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI). Compared to all other imaging techniques, MRI is efficient in the application of brain tumor detection and identification, due to the high contrast of soft tissues. Computer-aided detection or diagnosis (CAD) system effectively detects and diagnoses the cancer in their early stages.CAD systems can play a key role in the early detection of cancers and helps to reduce the death rate with cancer. Hence CAD systems and related techniques have attracted the attention of both research scientists and radiologists. CAD is nothing but the procedures in medical science that assists the doctor in the interpretation of medical images. Imaging techniques in X-ray, CT, MRI, and Ultrasound diagnostics yield a great deal of information, which the radiologist has to analyze and evaluate comprehensively in a short time.

II. RELATED WORK

1] A computer based method for defining tumor region in the MRI brain images is presented by *V.Amsaveni, et*. [2]. In this paper, a brain tumor detection method using preprocessing, Gabor feature extraction and BPN classification is proposed. The features are used to train and classify the brain tumor employing Artificial Neural Network classifier. The system can be tested with different images. The experiment result shows the classification accuracy of 89.9%.

2] The traditional method for detecting the tumor diseases in the human MRI brain images is done manually by physicians. Automatic classification of tumors of MRI images requires high accuracy, since the non-accurate diagnosis and postponing delivery of the precise diagnosis would lead to increase the prevalence of more serious diseases. To avoid that, an automatic classification system is proposed for tumor classification of MRI images[7]. This work shows

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 6, Issue 4, April 2018

the effect of neural network (NN) and K-Nearest Neighbor (K-NN) algorithms on tumor classification. The results show that this approach achieves 100% classification accuracy using KNN and 98.92% using NN.

3] *D.Shridhar, IV.Murali Krishna* [8] used the Probabilistic Neural Network with Discrete Cosine Transform for Brain Tumor Classification. Decision making was performed in two steps, i) Dimensionality reduction and Feature extraction using the Discrete Cosine Transform and ii) classification using Probabilistic Neural Network (PNN). Evaluation was performed on image data base of 20 Brain Tumor images. The proposed method gives fast and better recognition rate when compared to previous classifiers. The main advantage of this method is its high speed processing capability and low computational requirements.

4] *Shobhana,et*[9] made a comparative study of transform techniques namely Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT) each separately combined with the Probabilistic Neural Network (PNN) is used for the classification of brain tumor. The system consists of 3 stages for the diagnosis of brain tumor. In the first stage, MR image is obtained and preprocessing is done to remove the noise and sharpen the image. In the second stage, DCT and DWT is used for feature extraction .In the third stage, Probabilistic Neural Network with Radial Basis Function distinguishes brains abnormality. Finally the performance of DCT and DWT in diagnosing the brain tumor is compared using the parameters such as sensitivity rate and precision rate.

5] It is of great importance to early detect abnormal brains, in order to save social resources. However, potential of wavelet decomposition is not fully explored and widely used. The wavelet-energy was a successful feature descriptor that achieved excellent performance in various applications. The approach from *Sahar Ghanavati ,et*[10] consisted of a three-stage system, including wavelet decomposition, energy extraction, and support vector machines. The results of proposed approach showed its performance was comparable with state-of-the-art algorithms. In addition, it provided a new means to detect features indicative of abnormal brains.

In this study, a new approach for automatic classification of MR Images as normal or abnormal using Wavelet-Energy and SVM is proposed. The results show that the proposed method gives comparable results with latest methods presented in the literature, but the proposed approach gives a specificity of 100%. It suggests that three-step algorithm is a promising for image classification in a medical imaging application. This automated analysis system, which requires much lighter computational time, could be further used for classification of image with different pathological condition, types and disease status.

III. METHODOLOGY

The system for tumor detection from MRI brain images is shown in figure 1. It involves preprocessing, feature extraction, classification with neural network training.

The block diagram for proposed system is as follows-

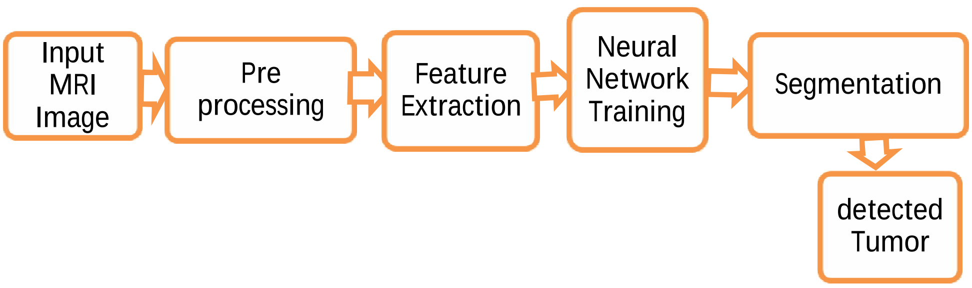


Fig 1. Block diagram of the system

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 6, Issue 4, April 2018

A] Preprocessing:

The input MRI images acquired for brain tumor detection are preprocessed to improve the accuracy of tumor detection.

All dataset images are resized to 256 x 256 . All RGB images are converted to gray scale images.

B] Feature Extraction:

Features extraction are identifying relevant features leads to faster easier, and better to understand images. Feature extraction affects significantly the quality of the classification process. MRI texture contains a rich source of information such as characterize brightness, slope, size, and other features[3][4] .After the preprocessing stage various texture features such as entropy, standard deviation, kurtosis etc. are extracted from the images. Wavelet Transform is capable of representing textures at the most suitable scale.

1] Discrete Wavelet Transform:

Wavelet transform performs multi–resolution of images that is simultaneous representation of images on different resolution levels. The wavelet compression techniques uses wavelet filters for decomposition into sub images. First, filter is applied along the rows and then along the columns thus resulting in four sub-bands as low-low, low high, high-low and high- high. Hence, M x N image is filtered and then down sampled into N x M/2 images. Then each column is filtered and down sampled into N/2 x M/2 images. Wavelet decomposition provides four sub bands, which are as follows-

1. Approximated (LL) 3. Vertical (HL)

2. Horizontal (LH) 4. Diagonal (HH)

Approximated sub band (LL) is normally further decomposed at different scales while three sub bands (LH, HL, HH) include characteristic of an image. DWT overcomes the drawback of Cosine transform by recognizing point discontinuities in image. Discrete Wavelet transform provides information about local frequency.

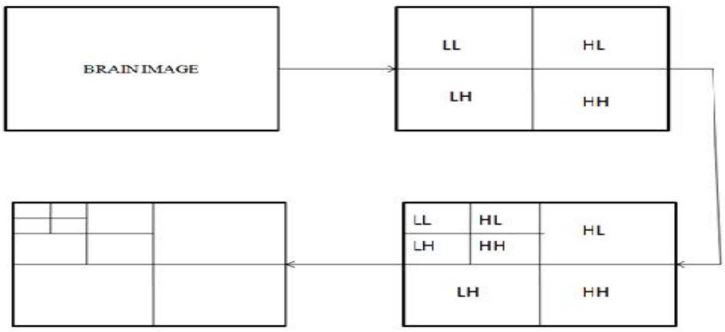


Fig. 2. Basic Decomposition Steps for Image

2] GLCM [Gray level Co-occurrence Matrix]-

Texture is defined as a function of the spatial variation in pixel intensities. The GLCM and associated texture feature calculations are image analysis techniques. Gray-level pixel distribution can be described by second-order statistics such as the probability of two pixels having particular gray levels at particular spatial relationships. This information can be depicted in 2-D gray-level co-occurrence matrices, which can be computed for various distances and orientations. In order to use information contained in the GLCM, Haralick defined some statistical measures to extract entropy, contrast, correlation and energy. GLCM is a tabulation of how often different combinations of gray levels co-occur in an image or image section. Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity at the pixel of interest.

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 6, Issue 4, April 2018

Energy: Measurement used to measure uniformity.

$$\sum_{i,j=0}^{N-1}(P_{i,j})^2$$

Homogeneity: Measurement of degree of variance.

$$\sum_{i,j=0}^{N-1}\frac{P_{i,j}}{1+(i-j)^2}$$

Correlation: To measure correlation between pixel values and its neighborhood.

$$\sum_{i,j=0}^{N-1}\frac{(i-\mu)(j-\mu)}{\sigma^2}$$

Entropy: Measurement of randomness.

$$\sum_{i,j=0}^{N-1}P_{i,j}(-ln\ (P_{i,j}))$$

C] Classification: Classification is a computational method used to find patterns and develop classification schemes for data in very huge datasets.

1. Probabilistic Neural Network (PNN) : Is a Radial Basis Neural Network, which provides a general solution to pattern classification problems by following an approach called Bayesian classifiers. It is employed to implement an automatic MR image classification of brain tumors into normal and Abnormal.

Probabilistic Neural Network has three layers, as shown in fig.3, the Input layer, Radial Basis Layer and the Competitive Layer. Radial Basis Layer evaluates vector distances between input vector and row weight vectors in weight matrix. These distances are scaled by Radial Basis Function nonlinearly. Then the Competitive Layer finds the shortest distance among them, and thus finds the training pattern closest to the input pattern based on their distance.

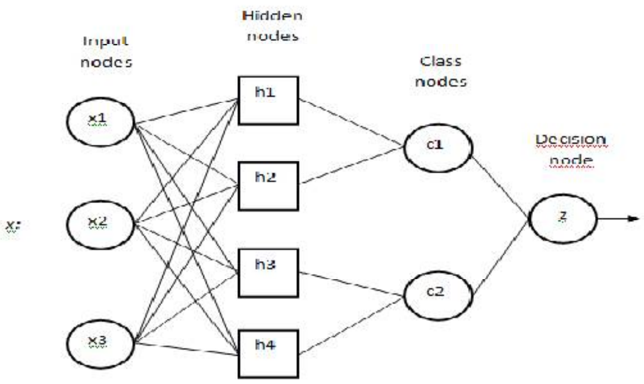


Fig 3. Architecture of a Probabilistic Neural Network

A PNN is predominantly a classifier since it can map any input pattern to a number of classifications. The main advantages that discriminate PNN are, its fast training process, an inherently parallel structure, guaranteed to converge to an optimal classifier as the size of the representative training set increases and training samples can be added or removed without extensive retraining. Accordingly, a PNN learns more quickly than many neural networks model and have had success on a variety of applications . Based on these facts and advantages, PNN can be viewed as a supervised neural network that is capable of using it in system classification and pattern recognition. The probability can be estimated using the formulae.

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 6, Issue 4, April 2018

2.Trained PNN Overview:

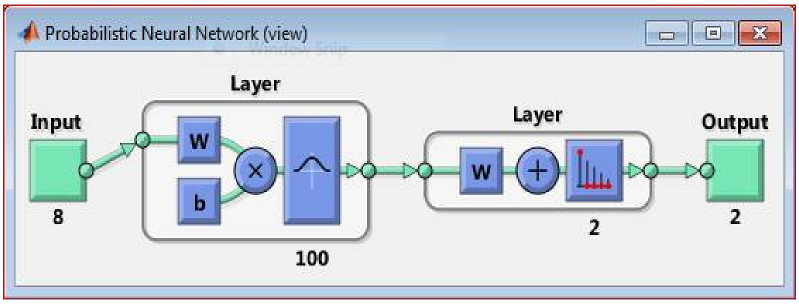
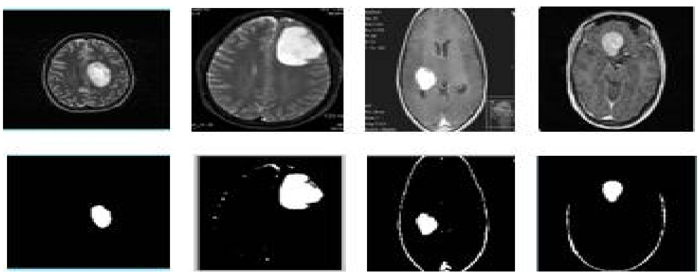


Fig 4. Overview of PNN

D] Segmentation:

The main aim of the segmentation is to extract useful information from the image. Cluster analysis is the official learning methods and algorithms for grouping objects according to characteristics or similarity. Clustering is a way to separate groups of objects. Cluster analysis does not use class labels. Fuzzy c-means (FCM) is a data clustering technique in which a dataset is grouped into n clusters with every datapoint in the dataset belonging to every cluster to a certain degree. For example, a certain datapoint that lies close to the center of a cluster will have a high degree of belonging or membership to that cluster and another datapoint that lies far away from the center of a cluster will have a low degree of belonging or membership to that cluster. The output for segmentation can be seen as-



Segmented Results ->

Fig5. 1] 1st row- input images 2]2nd row- Respective segmented output

IV. PERFORMANCE VALIDATION

To validate the performance of the system this paper used four statistical measures of the performance of a binary classification test. Sensitivity, Specificity, Precision and F-measure are all defined in relation to the possible outcomes of the classifier system. When we attempt to classify an image, there are four outcomes viz. True Positive, True Negative, False Positive, False Negative. True Positive is the condition when cancerous cells are identified as cancerous cells, False Positive is the condition when non-cancerous cells are identified as cancerous cells, True Negative is the condition when non-cancerous cells are identified as non-cancerous cells and False Negative is the condition when cancerous cells are identified as non-cancerous cells.

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 6, Issue 4, April 2018

Table 1: Result of testing images

For Test for 30 Image		
Result ↓	Normal	Abnormal
No.of Images	10	20
Normal	10	1
Abnormal	0	19

Table 1 describes the results for test images . Out of 30 test images 10 are normal and all classified correctly, remaining 20 are of abnormal images out of which 19 classified correctly. The values are obtained for TP, TN, FP and FN respectively are substituted in formulae given below to calculate values for parameters such as sensitivity, specificity etc.

Table 2: Parameters for Performance Evaluation

Parameters	Formulae	Results
Sensitivity - also called as recall denotes the test's ability to identify positive results.	TP / (TP + FN)	95.00%
Specificity - denotes the test's ability to identify negative results.	TN / (TN + FP)	100 %
Precision - gives the proportion of subjects with positive results who are correctly identified.	TP / (TP + FP)	100 %
F-measure – is a metric that gives the harmonic mean of Precision and Sensitivity. It is the overall classification performance.	$\frac{2\ x\ Precision\ x\ Sensitivity}{\text{Precision + Sensitivity}}$	97.43 %

Table 2 describes about the parameters that are required to calculate performance evaluation. The results are also shown in the table. The values that are obtained for TP, TN, FP and FN respectively are substituted in the formula in order to calculate values for each parameter. Depending on formula the results are obtained.

V. EXPERIMENTAL RESULTS

The proposed technique has been experimented on Images obtained from Local Laboratories. MRI images of size 256x256 are considered for evaluation. We have considered 100 images for our database., from which 65 images were of Abnormal and 35 images were of normal . Out of the total 100 images, 70 images were used for training system and 30 are used for testing system performance. System gave an accuracy of 100% for training & 96.66% for testing images .To see the effectiveness of the developed algorithm, we performed on real time images that were obtained from the local hospital. These images were passed through our system and observed that the system gave an accuracy of 96.66%. The presented system not only enables the classification of whole images but also presents a better performance for sub images when compared with some of the existing systems. Therefore it is concluded that PNN is a Powerful classifier in future because of its high speed computational capability ,guaranteed output and also samples can be added without any extensive training. Only the requirement is database should be large as possible.

VI. CONCLUSION

Method introduced one automatic brain tumor detection method to increase the accuracy and decrease the diagnosis time. PNN is a challenging classifier in future. The system can be tested with different images. It is essential to use large number of patient's data which will improve the accuracy of the system. Performance validation is measured by standard methods which gives an accuracy of 96.66 %. The purpose is to develop tools for discriminating the two classes normal and abnormal from MRI images and assist on decision making in clinical diagnosis and this will help

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 6, Issue 4, April 2018

doctor to take or analyze in which stage of cancer the patient have and according to which he/she can take necessary and appropriate treatment steps.

REFERENCES

1] M. T. Hagan, H. B. Demuth, and M. H. Beale, Neural network design. PWS Pub, 1996.
2] V.Amsaveni, N.Albert singh, "Detection of brain tumor using neural network," IEEE-31661.
3] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification," IEEE Transactions on Systems, Man and Cybernetics, vol. 3(6), Nov. 1973, pp. 610-621, doi:10.1109/TSMC.1973.4309314.
4] R. M. Haralick, "Statistical and structural approaches to texture,". Proceedings of the IEEE, vol. 67(5), May 1979, pp. 786-804, doi: 10.1109/PROC.1979.11328.
5] Akram M.U, Usman M, "Computer aided system for brain tumor detection which described Magnetic resonance (MR) image", IEEE Trans, on Biomedical Engg, Vol 3, No5.pp. no. 299 - 302, 2011.
6] D.F Specht, "Probabilistic Neural Networks", Vol.3, No 1,pp. 109-118,1990.
7] Amer Al-Badarneh, Hassan Najadat , "A Classifier to detect Tumor Disease in MRI Brain Images" IEEE/ACM International conference on Advances in social Networks Analysis And Mining,2012.
8] D.Shridhar, IV.Murali Krishna, "Brain Tumor Classification Using Discrete cosine Transform and probabilistic Neural Network " International conference on signal processing, image processing and pattern Recognition [ICSIPR], 2013.
9] Shobhana G,Ranjith Balakrishnan, "Brain Tumor Diagnosis From MRI Feature Analysis-A comparative study",IEEE sponsored 2nd International conference on Innovations in Information Embedded and communication systems ICIIECS',2015.
10] Sahar Ghanavati, Junning Li, Ting Liu, Paul S.Babyn, wendy Doda, George Lampropoulos, "Automatic Brain tumor Detection in magnetic resonance images",IEEE-2012.
11] Othman, Mohd Fauzi, and Mohd Ariffanan Mohd Basri. "Probabilistic neural network for brain tumor classification." Intelligent Systems,Modelling and Simulation (ISMS), 2011 Second International Conference on.IEEE,2011.