Detection and Classification of Brain Tumor in MRI Images

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Abstract –Brain tumor detection in Magnetic Resonance Imaging (MRI) is important in medical diagnosis because it provides information associated to anatomical structures as well as potential abnormal tissues necessary for treatment planning and patient follow-up. In this paper a brain tumour Detection and Classification System is developed. The image processing techniques such as pre-processing, image enhancement, image segmentation, morphological operations and feature extraction have been implemented for the detection of brain tumor in the MRI images. In this paper, extraction of texture features in the detected tumor is achieved using Gray Level Co-occurrence Matrix (GLCM).BPNN and K-NN classifier is used to classify MRI brain image into abnormal and healthy image.

Keywords- BPNN, GLCM, K-NN, Morphological operator, Segmentation

1. INTRODUCTION

Brain tumour is one of the major causes of death among people. Brain tumor is cluster of abnormal cells growing in the brain. It is possible that the chances of survival can be increased if the tumor is detected and classified correctly at its early stage. Detection of these tumours from brain is very difficult at the regions where a tumour is overlapped with dense brain tissues. Visual detection of these abnormal tissues may result in misdiagnosis of volume and location of unwanted tissues due to human errors caused by visual fatigue. Nowadays, automatic brain tumour detection in MRI images is very important in many diagnostic and therapeutic applications.Automated classification and detection of tumours in different medical images is motivated by the necessity of high accuracy when dealing with a human life. In this paper the designed system is developed for Detection and Classification of Brain tumour from a given MRI image of tumour affected patients.

Magnetic Resonance Imaging (MRI) is a medical imaging technique used to visualize the internal structure of the body and provide high quality images. MRI images do not involve exposure to radiation, so they can be safely used in people who may be vulnerable to the effects of radiation, such as pregnant women and babies.Brain tumours are classified into primary brain tumour and secondary braintumour.Primary tumours are tumours that originate in the brain itself, secondary brain tumours are the cancer cells that originate from another part of the body and have spread to the brain.This paper presents approach for feature extraction and classification of brain tumor [1][2].

2. METHODOLOGY

The method involves processing of MRI images that are affected by brain tumor for detection and classification of brain tumors. The image processing techniques like preprocessing, segmentation, morphological operator are used for the detection of tumor and then texture feature extraction method is used for extracting features from the MRI image. Features are extracted using Gray Level Co-occurrence Matrix. After feature extraction BPNN and K-NN Classifier is used for the classification of brain into normal and abnormal images. The methodology used for MRI brain images is as shown in Fig. 1

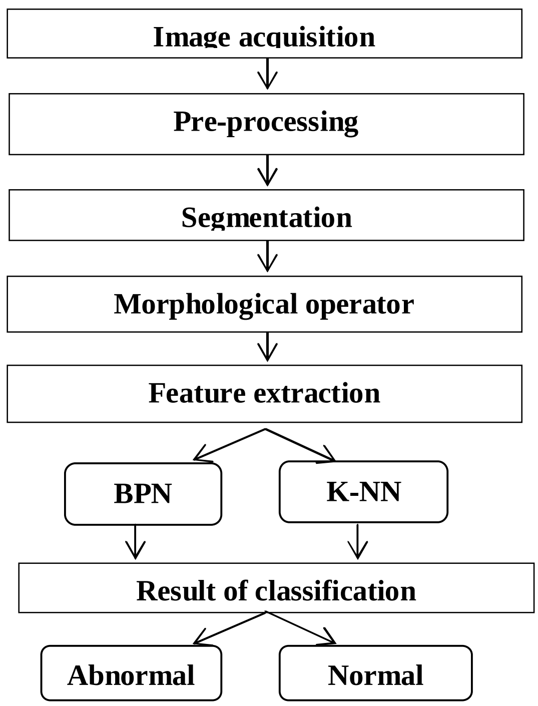

Fig 1: Block diagram of the system

2.1MRI Image database[6]**:**MRI image database consists tumor brain images and normal brain images. These images are collected from MRI scan center. The samples of MRI brain images are shown in following Fig 2

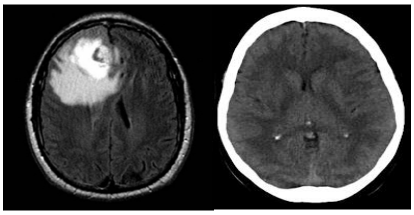

Fig 2 Samples of MRI images

These Images are stored in MATLAB and displayed as a gray scale image of size 256*256.

2.2 Image Pre-processing

This step is carried out to improve the quality of the image to make it ready for further processing. This improved and enhanced image will help in detecting edges and improving the quality of the overall image. Edge detection will lead to finding the exact location of tumor. Following steps are used in the preprocessing stage:

a) Noise Removal: In medical image processing, medical images are corrupted by different type of noises. It is very important to obtain precise images to facilitate accurate observations for the given application. In this paper noise reduction has done on an image by filtering or by wavelet analysis.

b) Image Enhancement: Image enhancement is basically improving the interpretability or perception of information in images for human viewers and providing `better' input for other automated image processing techniques. The principal objective of image enhancement is to modify attributes of an image to make it more suitable for a given task and a specific observer. During this process, one or more attributes of the image are modified.Filtering is technique for enhancing the image.

2.3 Segmentation:

Image segmentation is based on the division of the image into regions. Division is done on the basis of similar attributes. Similarities are separated out into groups. Basic purpose of segmentation is the extraction of affected regions from the image, from which information can easily be perceived. Thresholding is used for segmentation as it is most suitable for the present application in order to obtain a binarized image with gray level 1 representing the tumor and gray level 0 representing the background.

Threshold Segmentation: Thresholding often provides an easy and convenient way to perform the segmentation on the basis of the different intensities or colors in the foreground and background regions of an image. A thresholding operation is applied typically on a greyscale or color image.Thresholding method is based on a clip-level or a threshold value to turn a gray-scale image into a binary image. Black pixels correspond to background and white pixels correspond to foreground. If the pixel's intensity is higher than the threshold, the pixel is set to white, in the output. If it is less than the threshold, it is set to black. Segmentation is accomplished by scanning the whole image pixel by pixel and labeling each pixel as object or background according to its binarized gray level.

2.4 Morphological Operators:

After converting the image in the binary format, morphological operations are applied on the converted binary image. The purpose of the morphological operators is to separate the tumor part of the image. Now only the tumor portion of the image is visible, shown as white color. This portion has the highest intensity than other regions of the image.The erosion operator is used to shrinks object in images. A structuring element of disk operator is used to perform erosion operation.

2.5 Feature Extraction [1],[3]**:**

Features are said to be properties that describe the whole image. The purpose of feature extraction is to reduce the original dataset by measuring certain features. GLCM matrix features are used to distinguish between normal and abnormal brain tumors. GLCM is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, in the image.. Five co-occurrence matrices are constructed in four spatial

Orientations horizontal, right diagonal, vertical and left diagonal (0°, 45°, 90°, and 135°). A fifth matrix is constructed as the mean of the preceding four matrices. Texture features (Grey Level Co-occurrenceMatrix Features)from each co-occurrence matrix, a set of sixfeatures areextracted in different orientations for the training of theclassifier. Let p be the N*N co-occurrence matrix, calculated for each sub-image, then the following statistical texture features are calculated:

1. Energy (E): Energy measures textural uniformity i.e. Itmeasures pixel pairs repetitions

E=$\sum_{i,j} p(i,j)$^2……….(1)

2. Contrast: It a measure of the intensity contrast between a pixel and its neighbor over the whole image. Contrast is 0 for a constant image.

Contrast=$\sum_{i,j} mod(i-j)^2\, p(i,j)$ …….. (2)

Where, p(i,j) is pixel at location (i,j)

3. Entropy (EN): It is a measure of randomness.

EN=$\sum_{i,j=0}^{N-1} p(i,j) log_2$p (i,j) .... (3)

Where, N is no. of different values which pixels can adopt.

4. Homogeneity (HOM): Itmeasures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

HOM=$\sum_{i,j} p(i,j)$/ (1+mod (i-j)) .... (4)

5. Inverse Difference Moment (IDM): It is the measure of local homogeneity.

$$IDM=\sum_{i,j} \frac{1}{1+(i-j)^2} * p(i,j) \quad \text{..........} (5)$$

6**. Dissimilarity:** Dissimilarity is similar to GLCM contrast and it is high if the local region has high contrast.

$$\text{Dissimilarity} = \sum_{i,j=0}^{G-1} |i-j| p(i,j) \text{.........} (6)$$

Where G is number of gray levels used in image.

2.6Classification:

Classification is a computational method used to findpatterns and develops classification schemes for data in very huge datasets. Classification is the process where a given test sample is assigned a class on the basis of knowledge gained by the classifier during training. Its task is to assign an input pattern represented by a vector to one of many pre-specified classes. In this paper BPNNand K-NN classifier is used for the classification of brain MRI image into healthy brain or Tumour brain

2.6.1 K-Nearest neighbour classifier

The K-nearest neighbor (KNN) classification rule is one of the most well-known and widely used nonparametric pattern classification methods. The k- nearest neighbor classifier is a simple supervised classifier that has yield good performance for optimal values of k. This classifier computes the distance from the unlabeled data to every training data point and selects the best k neighbors with the shortest distance. In this work, the Euclidean distance is used for distance metric K-NN estimation is based on searching for the K closest (nearest) samples within a set of training samples (neighbours) to a test sample from the same type. K-NN classifier computes distances between a test sample (feature vector) and all training samples, and then Ksamples, out of *n* training samples, that are closest to test sample are subjected to majority voting to choose the class. Euclidean distance is the measure of distance between a test sample and samples of a training set. For N-dimensional space, Euclidean distance between any two samples or vectors P and Q is given by.

$$D = \sqrt{\sum_{i=1}^{N} (Pi - Qi)^2} \text{...........} (7)$$

Where Pi and Qi are the coordinates of Pand Qin Dimension.

2.6.2Back propagation neural network

BPNN (Back propagation neural network) consist of an interconnection of simple components referred to as neurons, which are programming constructs that mimic the properties of biological neurons. BPNN consist of one or more layers. Each layer has one or more neurons. The neuron (perceptron) can be defined simply as a device with many inputs, one output, and an activation function. Following Fig 3 shows the neural network architecture.

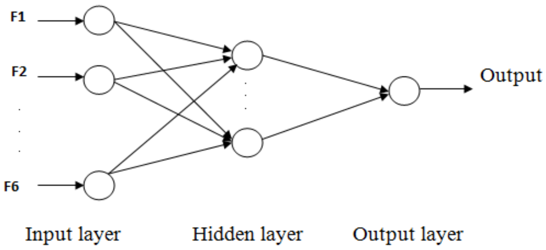

Fig. 3 Neural network architecture

Algorithm stages for BPNN:
1. Initialization of weights
2. Feed forward
3. Back propagation of Error
4. Updating of weights and biases

During the first stage' which is the initialization of Weights, some small random values are assigned. During feed forward stage each output unit receives an input signal and transmits this signal to each of the hidden units. Each hidden unit then calculates the activation function and sends its signal to each output unit. The output unit calculates the activation function to form the response of the net for the given input pattern.

In this paper the input layer consistsof six neurons corresponding to the six features. Theoutput layer consists of one neuron indicating whether theMRI is a candidate circumscribed tumor or not, and thehidden layer changes according to the number of rules thatgive best recognition rate for each group of features [5].

3. RESULTS AND DISCUSSION

The Methodology classifies the input MRIimage of brain into normal and abnormal images. The extracted part of tumor of brain images is as shown in following Fig 4

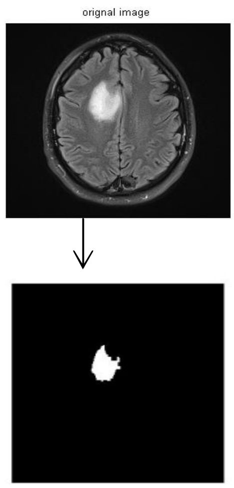

Fig 4: Tumor detected from a Tumor brain MRI image

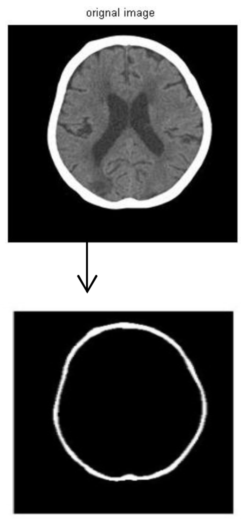

Fig 5: Tumor notdetected from a normal brain MRI image

Six features areextracted of normal and abnormal brain images using GLCM. Extracted features valuesabnormal images are shown in following Table 1

GLCM Parameter	Abnormal image	Normal Image
Energy	3.73E+09	4.23E+09
Contrast	348	64.5
Entropy	306287.4	313126.3
Homogeneity	64978.5	65120.25
Inverse difference moment	64978.5	65120.25
Dissimilarity	348	64.5

Table 1: GLCM Statistical feature values

The Extracted feature is used to train the BPNN and K-NN Classifier.20 images (10 abnormal and 10 normal) are used to trainthe Back propagation neural network and K-NN Classifier which classify the MRI brain images into normal and abnormal images.

3.1 Classification using K-NN classifier:

The accuracy by using K-NN classifier based on searching for the different K closest (nearest) samples is as shown in following Fig 6.The experimental results show that maximum accuracy level achieved for seen images are 100% and for unseen images are 70%.

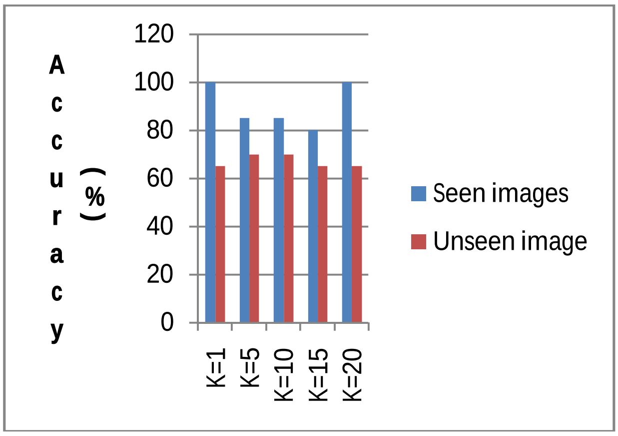

Fig 6: Accuracy using K-NN classifier for different K nearest samples

3.1 Classification using BPNN classifier:

Theaccuracy by using BPNN classifier at the different epochs as shown in following Fig 7.The experimental results show that maximum accuracy level achieved for seen images are 100% and for unseen images are 72.5%.

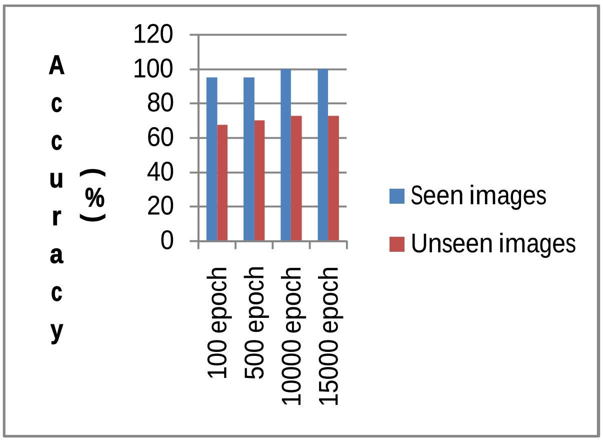

Fig 7: Accuracy by using BPNN classifier for different epochs

4. CONCLUSION

In this paper, classification technique is developed to classify between normal and abnormal brain images.Morphological operator is used for the extraction of tumour part. Textures features are used in the training of classifier.The extracted features of MRI are used as input to the BPNN and K-NN.Twentyimages (10 abnormal and 10 normal) are used to train the Back propagation neural network and K-NN Classifier. Forty unseen images are tested using BPNN and K-NN classifier. The experimental results show that Accuracy achieved by using K-NN classifier is 70 %.and by using BPNNclassifier is72.5%.

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